An investigation into Statistical Modelling of Data from Longitudinal Studies for the study of Educational Attainment and Development: A case study using The British cohort Study of 1970

Rosemary McNiece
October 2005

This thesis is submitted in partial fulfilment of the requirements of Kingston University for the award of Doctor of Philosophy in Applied Statistics.

Abstract

An investigation into Statistical Modelling of Data from Longitudinal Studies for the study of Educational Attainment and Development

Social inequalities in educational attainment are widely reported despite educational reforms aimed at providing equal educational opportunities for all. Variation in attainment between different socio-economic groups is apparent in the early stages of education, at primary level, and continues through compulsory into further and higher education. Many research studies have investigated the effects of social factors at different points in the education system but there is less research into how such influences develop throughout the school career and into adult life. Much education research now focuses on investigating educational progress and the factors that have an impact on attainment and progression throughout the education system.

The research presented here has two related and equally important aims. The first is to investigate appropriate statistical modelling techniques for the analysis of education data, in particular for examining educational attainment and progress. However, progress is a dynamic concept and can only be examined using longitudinal data. The increasing availability of large scale longitudinal data, on a national basis, provides new opportunities to explore the effects of social and other factors on educational progress. Hence the second main aim of this research is to investigate the scope of national longitudinal studies for examining the changing and developing effects of influential factors, such as social background and school, on educational attainment and progress. The statistical modelling techniques are applied to data from one such study, the British Cohort Study of 1970, and the analyses provide a case study to illustrate how education data from longitudinal studies can be investigated. The findings from the analyses are compared against current and existing research in order to evaluate the potential of data from national birth cohort studies for the investigation and monitoring of socio-economic trends in educational attainment and progression.

Contents

Chapter 6 : Log linear modelling of BCS70 data.

Chapter 7 : A multinomial logistic model for ordinal education outcomes.

Chapter 8 : Discussion and Conclusions

Introduction

Background to Research

The investigation of change over time is a key aspect of social science research in general. In education the impact of time on social trends plays a significant role in trying to understand why social inequalities in attainment still exist despite efforts to provide the same educational opportunities for all. A key area of current research is educational progress and evaluation of the effects of home, school and life experiences on overall attainment and progression through the education system.

Attainment and progress are distinct concepts. Attainment can be measured at any point in time without reference to what has gone before but in order to measure progress longitudinal data are required (Plewis 1997). The increasing availability of longitudinal educational data from a variety of sources, such as national cohort studies would seem to provide an ideal resource for longitudinal education research. These combined with accessible and appropriate methodologies for analysing such data provide opportunities for monitoring and evaluating the impact of social background factors and life experiences on educational progress and life long achievements.

Aims of research

The research presented here has two main aims. Firstly, in order to understand how background and life experiences affect attainment and progress, some form of statistical modelling is necessary so that factors can be considered in combination rather than individually. A main aim of this research is to investigate appropriate statistical modelling techniques for analysing the effects of social background and life experiences on educational attainment and progress. Secondly, the techniques are applied to data from the British Cohort Study of 1970 (BCS70), a national longitudinal birth cohort study, to investigate the scope of national longitudinal data sets for measuring and monitoring the effects of social factors on attainment and progression throughout the education system.

The following chapters outline the steps involved in this kind of analysis and some of the issues that are encountered in the process. The findings of the analyses are compared against existing relevant research and show that data from national longitudinal studies do provide a valid resource for investigating attainment and progress. On the whole the findings agree with existing research and also highlight some subtle trends in progress that are not widely reported elsewhere.

Plan of report

The following chapters provide an account of the various stages involved in the analysis, from preliminary investigations through to the findings from statistical analyses of BCS70 data. In the process many of the issues and problems that arise in using longitudinal data for education research are encountered and managed.

The first two chapters provide the background to the two main aspects of the research. Chapter one provides a brief history of education reform in post war Britain with particular emphasis on the period up to and including BCS70, and outlines current issues in the education research field. Chapter two provides a discussion about statistical analysis of education and longitudinal data and some of the problems that can be encountered in the process.

The data set used in the research, (BCS70), is described in chapter three. The chapter also provides details of the investigation of missing data. This is one of the first stages in analysing social survey data and the aim is to check that the sample is and remains representative of the population about which inference is being made. If left unchecked, missing data can cause a reliable and representative sample to become biased and non representative. Hence conclusions drawn from any subsequent analyses may be invalid. The BCS70 sample is examined on key social variables to ensure that the social structure of the sample remains more or less in tact throughout. Some methods for dealing with missing data that were used here are also discussed.

Statistical analysis of the data is then carried out in several stages. In chapter four preliminary investigations raise several important issues that must be resolved before any real analysis of the data can be carried out. For example it must be decided how best to measure overall attainment from the different education measures available. Preliminary analyses also help to identify the social factors that are most influential on attainment. Factors which have no or negligible effect or where there is too little information to consider in further investigations can also be eliminated at this stage. Subsequently preliminary investigations of the data provide the first indications of the how social factors affect educational attainment and of how these effects change over time. This process also raises the main problem in using BCS70 data for education research which is the fact that information about schools was not available for analysis when this research was carried out. Hence, school effectiveness, an important and major aspect of education research cannot be investigated. However the schools information has recently become available and the methods outlined in chapters five, six and seven could easily be extended to include this information.

Chapters five, six and seven present several different statistical methodologies for analysing the types of education outcomes found in BCS70 which are typical of education data in general. In chapter five the scope of multilevel modelling of the data is investigated. Multilevel models arise from the need to consider hierarchical structures in social data and are particularly suited to education data as they allow for the hierarchical nature of the education system. The effects of explanatory factors can be investigated at each level to give a more complete picture of where significant influences come from and how they affect attainment. Due to the lack of schools data multilevel modelling cannot be used to its full potential but the application is presented to show the capabilities of the technique in analysing the type of longitudinal data available in BCS70.

In chapter six a little known variation of log linear modelling is used for further investigations into the effects of social background factors on attainment and how these effects change and develop over time, an area often overlooked in education research. The analysis also demonstrates how different techniques are suitable for the different education outcomes found in a study such as BCS70, and highlights the difficulties that can be encountered in comparing attainment across different time points.

In chapter seven, progression and attainment in post compulsory education is investigated. A continuation ratio model is used to analyse the data as it is particularly suitable for the outcome variable in question. The continuation ratio model is not widely used in education research but the analysis presented here illustrates how it has much potential in the field.

Finally, chapter eight draws together the findings from the analyses and evaluates them in the context of both current general education research and existing research relevant to the BCS70 study period. The overall findings in terms of the main aims of the research are discussed and some ideas for future work are also proposed.

Chapter One : Education Reform and Research

1.1 Introduction

Education is fundamental to the development of society and it is generally perceived that a well-educated population leads to economic and social success. Successive governments have placed increasing emphasis on raising educational standards in the population as a whole and have initiated many education reforms with the aim of achieving better and more accessible education. Hence research into the many different aspects of the education system has expanded in the quest for a deeper understanding of the factors and processes that affect educational attitudes, aspirations and achievements.

Although educational opportunities for all sections of society have expanded since the middle of the last century it is well recognised that average educational attainment varies markedly between different social groups. Many studies have investigated the association between social factors and educational attainment and the findings of such investigations are often the spurs for education reform, much of which has been aimed at eliminating or at least reducing these inequalities. However there is evidence that social inequalities in educational attainment still exist in the U.K. population today (Bynner & Joshi 2002, Parsons & Bynner 2002, Gillborn & Mirza 2000). The evidence shows that the more socially disadvantaged sections of society have the lowest levels of attainment and subsequently tend to dominate less skilled and lower paid occupations in later life. Overall they can expect a lower standard of living than their more advantaged peers. This raises many questions as to why a population who are, in theory, exposed to the same education system, standards and opportunities achieve different standards of attainment by the end of their formal school years. Hence some understanding of the factors that influence overall attainment is required if equality of attainment across society is to be achieved.

The field of education research is vast and would be impossible to review in its entirety. This chapter provides a general overview of education reform in post war Britain from the earliest concepts of 'Education for all' through to the period covered by BCS70. This is followed by a brief synopsis of current trends in quantitative education research.

1.2 Education for All – the British education system in post war Britain

Before the early 1900s, education in Britain was mainly the domain of the more privileged and wealthier sections of society but the twentieth century brought about major Education reforms which were aimed at changing this trend. The reforms in the first half of the century (e.g. Balfour Act 1902, The Education Act 1918, Hadow report 1926, Spens report 1938) were concerned with widening the educational opportunities afforded to the whole of the British school age population. The ideology of 'Education for All' began to emerge.

The first real attempt to provide 'Education for All' in Britain came in the years following the second world war when the Education Reform Acts of 1944 (England and Wales), 1945 (Scotland) and 1947 (Northern Ireland) were introduced (collectively referred to as the 1944 Acts from here on). The 1944 Acts included many suggestions for improving the existing education system and for addressing social inequalities. Not all of the recommendations were implemented immediately or even in subsequent years but the fundamental principles associated with eliminating social bias and expanding access to secondary education (and beyond) have remained embedded in education policy since. The major changes that resulted from the 1944 Acts were, the setting up of a three stage education system, i.e. primary, secondary and further education and raising of the school leaving age to 15. It was intended that these changes would provide the same free and universal educational opportunities for all children up to age 15.

However the 1944 Acts were not as successful as anticipated and did not produce the universal levels of educational attainment nor the widening of opportunities for all groups of society that had been hoped for. By the 1960s there was no real marked improvement in overall educational outputs. For example, 'in 1961 73 per cent of students in England left school without ever having attempted a public examination while over 90 per cent of Scottish school leavers left at age 15 without any qualifications' (Jones 2003). Furthermore social, regional and gender inequalities in educational attainment and opportunity still existed within the population as a whole and there was little evidence of increasing opportunity for working class students. By the mid 1960s it was becoming obvious that just providing equal educational opportunities would not be sufficient to eradicate social inequalities in attainment. The education system was operating in a society which had deep social divisions and in order to address inequalities, a change in society's perceptions and attitudes towards education was needed. Reviewers concluded that although education was provided for all children up to age 15, not enough attention was paid to promoting education to the traditionally non educated social groups (Halsey et al. 1980) and the major problem still facing education was how it could be opened up to the working classes (Jackson & Marsden 1966).

In the twenty years after the war, British sociologists were largely concerned with widening access to schooling but Britain was changing in other respects that would impact on the education system. The population was changing both in size and demographics and the 1950s and 1960s saw a high level of immigration mainly from the Asian and Carribean colonies. Immigrant workers on the whole tended to be relatively uneducated, taking up jobs in the semi & unskilled social classes. The children of immigrants were attending British schools but they faced problems within the education system that native British children did not, such as language barriers and general social acceptance. Overall these ethnic minorities were low achievers at school and 'ethnicity' emerged as another social division in the education system. Such rapid changes in society meant that the intentions of the 1944 Act became increasingly important but the recommendations needed updating to reflect the changing population.

In response to the changing needs government expenditure on education increased rapidly during the 1950s, 1960s and early 1970s. At the same time Britain was becoming more economically successful and the demand for higher levels of education among the population increased. During the same period there was growing unease among those responsible for education; parents, teachers and politicians, about the opportunities afforded to the working classes, particularly in secondary education and from the mid 1960s some significant changes took place.

Probably the biggest of these changes was the introduction of comprehensive secondary education in response to concerns over the negative effects on 11 year old children of the selection process involved in the transition from primary to secondary education. Comprehensives replaced the selective system of secondary and grammar schools and by the end of the 1970s provided the near universal, non selective state schooling for 11-16 year olds, originally intended by the 1944 Acts. A further significant development was the introduction of a two tier examination system at age 16. In 1965 CSE examinations were introduced in England and Wales (an equivalent system had been operational in Scotland since 1962) to increase the opportunity for all students to gain some national certificate qualifications before leaving full time education. The CSE examination was specifically aimed at those who would have left school without qualifications otherwise and were intended to complement the existing GCE O level examinations.

At the beginning of the 1970s social inequalities in educational attainment were still widespread. Class, gender and ethnicity inequalities were at the forefront of concerns about underachievement. Large numbers of students were still leaving school without recognisable, measurable qualifications and in 1972 the school leaving age was raised to 16 with the aim of increasing uptake in examinations. An increase in the numbers staying in full time education and being entered for public examinations resulted.

The early 1970s also saw the emergence of new ideas about education methodologies and practices, with a shift in focus towards more philosophical ideas underlying the education process. One of the earliest of these new approaches was outlined in the Plowden report (1967) which focused on the pre-school years as the time when children are exposed to the most influence in forming ideas and opinions and as potentially crucial in determining future educational success. The Plowden report also presented new learning concepts, for example learning through 'activity and experience' rather than the storing of knowledge, during the early primary stages. Such ideas were not particularly well received in the education field at the time and the report received much criticism on the grounds that it lacked outcomes and was not directly related to the skills required in a future workforce. However, although few of Plowden's concepts were implemented on a national basis the report did much to broaden the debate about equal opportunity even at primary level.

The Ruskin speech (1976) is considered to be the turning point for education strategy in Britain, and was the first major directional alteration since the 1944 Acts. It marked the end of post war educational hypotheses stating that much of the reforms of the previous 30 years had not succeeded in doing what they had set out to do and highlighting discontent with the existing direction of education in Britain. The report dismissed the existing Schools Council claiming they had done nothing to reform the education system and called for "a time for change" and a new more centralised approach for the education system with government at the highest level was proposed.

Towards the end of the 1970s, issues of ethnic and gender inequalities in attainment were of increasing concern at a national level (Warnock report 1978). The effects of social class on educational opportunity took a back seat and were no longer a source of real concern among policy makers, even though within the state education system there was still a strong correlation between poverty and educational failure.

The tone of educational policy post Ruskin was very different to that of post war policy as it reflected a changing Britain. By the 1980s economic, social and demographic changes in Britain had altered the circumstances under which the education system worked (HMSO 1985). It was realised that in order to raise standards at all levels of ability, schools had to respond to changes beyond the education system.

Although education rates, in terms of examination entries and qualifications achieved, had improved by the early 1980s there was still a national problem of underachievement in secondary education with substantial numbers of children leaving school at the earliest opportunity with few and low quality examinations. Education policy began to focus more on the need for a change in the system to promote staying on in post compulsory education and for the need to produce school leavers with the skills required by employers. For example, the Technical and Vocational Enterprise Initiative (TVEI) for 16-18 year olds resulted from liason with employers and was aimed at advancing the bottom 40% who were reportedly being neglected. The courses aimed to cater for technical and vocational aspirations across social, gender and varying ability ranges.

The mid 1980s also saw a more curriculum focused drive within the education system aimed at achieving a more coherent curriculum across the board. The examination system had not changed since the introduction of CSE in 1972 and there was concern that employers distinguished between GCE and CSE. To simplify the system and in an attempt to make it fairer the 7 grade point GCSE was introduced in 1986 with the first roll out of exams in 1988 (the equivalent was introduced in Scotland in 1984). The GCSE allowed students with different abilities to be examined on the basis of suitably differentiated papers with an aim to eliminate the 'ability' label attached to the GCE/ CSE division and. (The BCS70 cohort were one of the last school years to be assessed under the old GCE/ CSE system).

By the 1980s immigration on the massive scale seen in the 50s and 60s had eased. Ethnic minorities in schools were mainly second generation and British born, i.e. the children of the original immigrants. However these ethnic minority children were still perceived as being underachievers in school to the extent that a major study into the educational need and attainment of ethnic minorities was undertaken to investigate 'How should the education system respond to ethnic diversity?'. The findings of the Swann report (1985) showed that overall ethnic minorities suffered the same deprivations, such as unemployment and poor housing as the white population, but more acutely. This was likely to be a result of the fact that for the most part ethnic minority immigrants in the post war years settled in large, highly populated, typically socially deprived urban areas. Hence ethnic minority disadvantage was confounded in the more general problem of social inequalities. The report also found that although educational response to ethnic diversity had been positive and well intentioned there had been a tendency towards trying to assimilate ethnic minorities into the culture of traditional Britain and this was questioned. In general ethnic minorities were found to have the same outlook as whites, viewing education as important and the only way forward to improved opportunities and upward mobility. The findings also highlighted the need to look beyond one specific factor when investigating social effects on educational attainment.

Further Education Reform Acts (ERA) followed in the later half of the decade. The ERA of 1988 was hailed by government and policy makers as the most important and far reaching piece of education law making for England and Wales since 1944. The overall aim of the 1988 Act was similar to that of the 1944 Act, to raise the quality of education for all pupils, but the approach was different. The 1988 reforms were aimed at modernising the education system to reflect changing Britain and encourage an education marketplace. The Act consisted of several components, the most significant being the introduction of a national curriculum for compulsory schooling. Central government powers were restored giving a clear message of the importance of education and the role of LEAs was subsequently limited in an attempt to decrease diversity. Accountability of teachers, an idea first suggested at Ruskin was also introduced. The idea of an education marketplace emerged whereby parents and children could select and apply to a school on the basis of ability and aptitude, and competition between schools was encouraged. Where the 1944 Act aimed to provide equal education for all and had failed to produce a homogeneous standard of service, the 1988 Act put emphasis on providing equality of opportunity rather than equality of achievement.

On the surface the reforms of the 1980s seem to have achieved improvements in attainment and by the mid 1990s secondary school statistics showed an overall rise in levels of attainment (HMSO, 1982 -1996). However this conceals a widening disparity between success rates in different social groups. By 1993, 33% of British children lived in poverty (Jones 2003) and the relationship between social disadvantage and underachievement seemed as strong as ever. A further Education Reform Act was implemented in 1993 and was based around the five 'great themes' of education, quality, diversity, increasing parental choice, greater autonomy for schools and greater accountability. These themes were based on the government's belief that offering greater diversity and more choice to pupils and parents, is the route to higher educational standards. Again the focus of reform seems to be moving away from 'Education for All' and social inequalities towards equal opportunities in education provision.

Education reform is and continues to be an unfinished business. The period since Ruskin has been described by Campbell (2001) as having three separate periods. The first ten years are portrayed as a time of gentle persuasion to change and the second decade (1987-1996) involved the introduction of standards and accountability such as league tables. The third and ongoing phase since 1996 has seen further reform aimed at reinforcing performance and accountability factors while concentrating on raising standards across all stages of the education system.

1.3 General findings from past and present education research

Increasing education reform in post war Britain has inevitably heralded an increase in research across all aspects of the education system. Variation in the educational achievements of different groups are well documented (Bynner & Parsons 2001, Gillborn & Mirza 2000, ALBSU 1993, GLARE 1988, Mortimore & Blackstone 1982, Wedge & Prosser 1973) and amongst the most commonly investigated aspects are gender, ethnic and social class trends in attainment.

Over the years, reports into gender differences in attainment have shown that historically boys achieved a higher overall level of attainment than girls, particularly in mathematics and science. However the last 25 years has seen attainment balance out between the sexes and in recent years girls have been outperforming boys overall (Gorad et al. 2001, Warrington & Younger 2001, Arnot et al. 1999). Current trends in attainment have resulted in much research aimed at addressing 'underachievement' in boys.

Similarly much has been written about the poorer attainment seen amongst ethnic minority children although there is a general consensus that this is more a symptom of social differences rather than any difference in ability. Historically ethnic minorities have tended to belong to the more socially disadvantaged sections of society (Gillborn & Drew 1992, Brewer & Haslum 1986, Craft & Craft 1983) and may have been at an added disadvantage educationally if English was not their first language. In Britain today most ethnic minorities are British born and so the problems faced by their parents generation would not be so marked. Some studies have shown that differences in attainment between children from different ethnic backgrounds decrease significantly when social factors such as disadvantage are taken into consideration (Haque & Bell 2001, Drew & Gray 1990, Blatchford et al. 1985).

Educational attainment has always differed among the different social classes (Paterson 1991, Heath & Clifford 1990, Blatchford et. al 1985, Mortimore & Blackstone 1982, Davie 1973). Research has examined many aspects of class and social deprivation but overall those from the more advantaged classes (RG's professional and managerial) achieve higher levels of attainment than those from the less advantaged classes (RG's skilled, semi-skilled and unskilled). This trend is still evident today (Bynner & Joshi 2002, Gillborn & Mirza 2000) despite all the reforms and initiatives aimed at addressing social inequalities in attainment. Social class is also strongly associated with other aspects of social background. In general the disadvantaged classes are more likely to experience the poorest housing conditions and more overcrowding in the home, poverty measured by low incomes and receipt of social security benefits, and disruptions like spending time in care and living in a one parent family, all of which have been associated with lower educational attainment (Sammons 1995, St.Clair & Osborn 1987, Essen 1979).

Research has also shown that background can affect a child's willingness and eagerness to learn, and the value they place on a good education. The evidence agrees with Plowden's ideas in showing that the pre-school years are in fact highly influential in forming educational attitudes and aspirations (Feinstein 1998, Blatchford et al. 1985). Parents' educational experiences are also influential and research has shown that children are more likely to progress to the higher levels of education if their parents also took the same route (Yeshanew et al. 2005, Bynner & Joshi 2002, Burnhill et al. 1990). However parents of disadvantaged children are more likely to have left school at the minimum leaving age and have, on average, a lower standard of educational qualification than those in the higher social class groups so once again the influence of parents' education could be interlinked with social class differences.

Research also shows that school based factors can have an affect on attainment (although such factors are not considered in this work). For example, influences from teachers, peers and aspects of the school environment itself such as class size, mixed or single sex classes, teaching methods and availability of resources have all been linked to attainment (Warrington & Younger 2001, Sammons et al. 1993, Gillborn & Drew 1992, Raudenbush & Willms 1991, Steedman 1983). Influences from within the school environment can be positive or negative, for example a child from a home where education is not considered valuable may be positively influenced by peers and teachers who place a higher value on education. However, in practice it is often the case that school catchments encompass the same social groups and types of home environments, particularly in inner city environments where disadvantaged families tend to live in the same area. In such situations a child may be more influenced by their peers and restricted social interaction may actually be detrimental.

1.4 Some current directions in Education Research

In the last thirty years the emphasis of education research has shifted more towards investigation of the underlying mechanisms that result in differential attainment between different social groups. This includes not only factors at the individual level but also factors from within the school environment. School based factors have been shown to have a significant impact on attainment (Warrington and Younger 2001, Sammons et al. 1993, Raudenbush & Willms1991, Brandsma & Knuver 1989) and the value added by schools makes an important contribution to attainment. Since the early 1980s school effectiveness has become a major part of education research (Hatcher & Thomas 2000, Thomas et al. 1995, Nuttall et al. 1989, Gray 1981). The investigation of school effects has been assisted during this period by the development of multilevel modelling (Jesson & Gray 1991, Goldstein 1987) a major development in the statistical modelling of education data (see chapter 5).

Another increasingly important aspect of education research is the investigation of educational development and progress through the various stages of the education system (Strand 2002, Yang & Woodhouse 2001, Sammons 1995, Plewis 1988) and of the factors that affect progress at the different stages. To date these associations have not been monitored throughout an educational life time, i.e. through all three levels of education but this may be possible using data from longitudinal studies which can provide individual educational histories. Examination of the development of the effects of social factors on attainment throughout the education career may help to broaden our understanding of the complex social mechanisms that determine why children from some social groups do better, educationally, than others.

In the research presented here the developing effects of social factors are examined across several educational transitions from primary through to tertiary education. This is achieved by the application of appropriate statistical methodologies to data from a national longitudinal data set, BCS70. The BCS70 data set provides education histories for a large sample of individuals who were educated during a time when education policy and practice were under much scrutiny. Comparison of the findings from this research against existing research from the same era should reveal whether such monitoring can provide further understanding of the influence of social factors on attainment and progression.

Chapter Two : Statistical and Longitudinal analysis in Education Research

2.1 Introduction

Modern education research uses both quantitative and qualitative analysis techniques for investigating a range of educational topics and both make valuable contributions to the education field. In this research the focus is on quantitative research, in particular the use of statistical modelling for analysing longitudinal education data. It is recognised that qualitative methods make a valuable contribution to the education arena, but as they are not employed here they are less relevant to the following discussions. Similarly we do not discuss the research area of 'evidence based practice' in education as it is beyond the remit of the work presented here.

This chapter provides a general non-technical overview of the use of statistical analysis in education research. The analysis of longitudinal data is also discussed with particular attention to longitudinal analysis of education data. Some of the issues and considerations arising therein are also discussed.

2.2 Statistical modelling in Education Research

The study of the effects of society on educational attainment is not new and associations between social factors and attainment are well documented. However the investigation and interpretation of these associations is more open to variation both in the methods used and in the conclusions drawn. Increasingly, research seeks to provide understanding of how social factors and life experiences can influence the level of educational attainment reached. In an attempt to determine causal mechanisms that underlie attainment the effects of all major explanatory factors should be considered together. Statistical modelling provides a means of doing so as it allows the effects of several explanatory factors to be considered simultaneously within a single analysis. The aim of such modelling in education is to measure and explain variability in educational achievements (Plewis 1997), for example, varying rates of educational progress amongst students, or variation in educational choices and achievements.

The statistical models that are used in education range from the basic through to the very complex. In practice though, basic descriptive statistics and standard modelling techniques are by far more common than advanced statistical applications. Some of the commonly used standard statistical techniques include multiple linear regression and logistic regression and while these methods are usually applied correctly they often involve making assumptions about the data, particularly the outcome variable, which are not always valid. A common example is the use of multiple regression techniques to analyse outcomes that are not strictly measured on continuous scales. In reality few education outcomes are measured on a strictly continuous scale but such can be assumed for scores that cover a wide range of values. The same assumption would be less valid for scores based on a small range of values (< 7 is a common yardstick, Plewis 1997). Another common education data type are categorical outcomes where attainment is measured by a level of attainment rather than a test score or similar measure. Such outcomes are often analysed using logistic regression techniques but in practice few attainment measures readily meet the assumptions without some manipulation and / or collapsing of the outcome variable. Valuable information may be lost in the process. Ordered categorical outcomes are also common and are found particularly in post compulsory education. Again such outcomes are usually modelled using standard linear modelling techniques but ideally analysis methods would reflect the 'ordinality of the measurement scale' (Bynner & Joshi 2002).

The choice of statistical model for analysing data should be led by the type of data being investigated and not by a technique being standard or familiar. For example, appropriate statistical models for ordinal categorical outcomes do exist but they are not frequently used in education research. The availability of powerful computers and statistical software packages facilitates the use of complex statistical methods with little trouble and so appropriate methods of analysis should be used. An aim of the research presented here is to investigate appropriate statistical methods for the analysis and interpretation of the types of educational outcomes typically found in longitudinal data.

The most notable development in statistical methodology for education research of recent times is multilevel modelling (Bock 1989, Raudenbush 1989, Goldstein 1987). This technique is particularly suitable for education research and has become increasingly widely used since the mid-eighties when software packages such as ML3 and MLn became available. Multilevel modelling is continually being developed and the capabilities of the techniques and software are constantly evolving. Recent developments include multilevel models for ordinal outcomes (Fielding et al. 2003, Plewis 2002).

2.3 Longitudinal Research

Longitudinal studies are those where individuals are measured repeatedly over a period of time. Study designs vary and result in different types of longitudinal data (Taris 2000, Diggle et al. 1994, Menard 1991, Goldstein 1979). Longitudinal birth cohort studies, such as the BCS70 used here, follow the same sample over time, collecting data at various time points. Usually similar measures are recorded at each follow up study providing a fairly consistent set of variables at each measurement occasion. Hence investigation into patterns of change, development and the causal mechanisms underlying such changes and developments may all be possible.

The analysis of longitudinal data is an area that has seen much development in recent years. It may involve examining relationships between similar or the same variables at different time points, or the investigation of developmental trends in relationships between variables, i.e. examining trends in relationships between variables over time. Many standard statistical methodologies have been adapted to facilitate the analysis of the different types of longitudinal data that exist (Hand & Crowder 1996, Dale & Davies 1994, Diggle et al. 1994, Aitken & Longford 1986). Advanced modelling methods are also applicable to longitudinal data but are largely unused in the social sciences (Lambert & Gayle 2004).

2.4 Longitudinal Analysis in Education Research

The investigation of educational development and progress is a major theme of current education research (Strand 2002, Yang & Woodhouse 2001, Sammons 1995). As progress is a dynamic concept, its requires longitudinal data for assessment, hence the use of longitudinal data is becoming increasingly widespread in the education field (Schagen & Schagen 2005, Bynner & Joshi 2002, Sammons et al. 1993). The aims of such studies are in line with much existing research in that identifying and examining factors that influence progress, for example social background and educational experiences, are of interest.

In the past educational change has often been investigated by comparing data from several cross sectional studies, for example, year on year changes in GCSE attainment. While such cross sectional comparisons are useful for examining general educational attainment trends at a distinct point in the educational career they do not reveal any information about development or progress up to this point. As Dale and Davies (1994) observed

> *"limitations of data and methods have confined researchers to cross sectional studies with many assumptions in the interpretation because nothing is observed preceding or succeeding the survey time point"*

In order to assess educational progress some allowance must be made for what has gone before in the analysis process. The best way of achieving this is by monitoring attainment on successive occasions, in other words by using longitudinal data. Furthermore, there will inevitably be unmeasurable variability between sample members when using different samples. When using longitudinal data such variation is eliminated as the same sample is used throughout. Education data collected in a longitudinal birth cohort study allows investigation into how and when social factors start to affect the learning process. Monitoring of how such associations develop throughout the education system is also possible. Therefore, as education is a continuing and progressive process, it would seem that longitudinal data is well suited to the study of educational development.

For the purpose of education research the timing of BCS70 follow up studies are well spaced occurring at important stages in the education system (chapter 3). At each collection point information about educational attainment and a range of possible explanatory variables was collected. There are two main approaches to analysing the data (Hand & Crowder 1996). The first is suitable when change at the individual level, i.e. progress, is of interest. Data can be investigated by incorporating attainment measures from more than one occasion in the analysis (chapter 5). Alternatively data from each collection can be analysed separately and then the results compared across time points. This approach is applicable when examining changes in trends over time is of interest (chapter 6), it does not provide any measure of changes within individuals.

A difficulty of the latter approach arises in determining comparable outcome and explanatory variables at each measurement occasion. For measures of educational achievement, it is reasonable to assume that the tests used at each follow up were of a standard appropriate to age and expected ability and therefore are comparable across time points. Defining an overall attainment measure at each occasion is more problematic (section 4.2) as there are many aspects of society, home, school and life experiences that have the potential to affect educational attitudes, aspirations and subsequently attainment. In practice some approximate measure of social background or some combination of several factors is used for analysis purposes (section 4.3).

2.5 Interpreting research findings - statistical significance and effect sizes

An important consideration in education research is interpretation of results in a meaningful and useful way. When presented with research findings educationalists and policy makers increasingly want to know is 'what does it mean? (Elliot & Schagen 2004)

Traditionally determination of "significant" effects has been based on statistical significance. Although widely used in analytical studies, opinions about the real value of such tests in social survey research vary. Some argue that while the tests are useful for indicating whether or not a relationship exists they are not always reliable for judging how important that difference is in practical terms. In practice, statistically significant explanatory variables do not always have a truly practically significant effect on the outcome (USGS 1999, McLean & Ernest 1998, Cohen 1994). Furthermore, when dealing with large samples which are typical of longitudinal data and certainly relevant to BCS70, statistical significance can be affected by sample size and even small, practically insignificant associations will be statistically significant which could in turn lead to misguiding results. However, in the absence of any other means of testing for the impact of explanatory factors, statistical testing is widely employed to explain the findings of analyses.

In reporting research findings the significance of associations should be judged within the context of the investigation and the reporting of 'statistical significance' should be relative to the study. However, there is a need for a more precise and standard method of evaluating the effects of influential factors in education but currently there is no standard for reporting such associations. Here measures such as effect sizes (Schagen & Elliot 2004, Ely 1999) may be useful. Although the idea of effect sizes is not new, the use of effect sizes in education research is still very much new and not yet common practice. Methods of calculating and reporting effect sizes are varied, but two major classes are standardised differences and variance accounted for indices (Elliot & Schagen 2004).
The reporting of effect sizes may play an important role in standardising research findings and in particular in interpreting the effects of influential factors on education outcomes in practical terms. They may also help to avoid mis and over interpretation of results where different interpretations can lead to misleading conclusions (Gray 2004). However, education researchers should not get carried away with the idea that effect sizes are an absolute solution to presenting and interpreting research findings in a universal way. Elliot & Sammons (2004) suggest

> '*Effect sizes may well prove very useful in certain contexts and can provide an additional indicator in the interpretation of statistical analyses, although they should not be seen as a statistical cure-all*'

Effect sizes are still at the developmental stage and so should be used cautiously in conjunction with statistical testing, not in isolation. Nevertheless, they could provide a first step towards evaluating the practical importance of effects. Routine use of effect sizes would be valuable in longitudinal research where data is analysed as repeated cross sections and the same relationships between socio-economic and educational attainment is investigated at each time point. It would provide a yardstick from which significant parameter estimates could be evaluated and compared between occasions.

In the analyses presented here, statistical significance and confidence intervals are used in preliminary investigations (chapter 4) to examine associations between social background factors and educational attainment. Statistically significant associations are viewed as an indication rather than proof of an association between pairs of variables. The use of effect sizes is illustrated for interpreting the results of multilevel models fitted in chapter 5. An alternative interpretation of the size of effects is used in chapters 6 and 7 where odds ratios are used to describe the nature and magnitude of associations between categorical explanatory factors and ordinal categorical measures of attainment.

2.6 Summary

Quantitative education research is an ongoing and fast developing area of the education field. Longitudinal research in education is one such developing area and recent years have seen an increase in the analysis of education data from national longitudinal datasets. The growing importance of longitudinal education research is evidenced by organised discussions devoted to disseminating current practice in the field (Lambert & Gayle 2004). The analyses presented in the following chapters illustrate some of the ways in which analysis of longitudinal education data can be achieved.

Chapter Three : Data (Preparation for analysis)

3.1 The 1970 British Cohort Study (BCS70)

Britain has a history of longitudinal cohort studies, for example, the 1946 Birth Cohort Study, the (1958) National Child Development Study (NCDS), the British Cohort Study of 1970 (BCS70) and most recently the Millenium study (Centre for Longitudinal Studies) which collect a wide range of information about the lives of large and representative samples of the population from childhood through to adulthood. The data used in this research comes from BCS70, which follows the lives of all those born in the U.K between 5th and 11th April 1970, inclusive. It originates from the British Births Survey (BBS), which was sponsored by the National Birthday Trust Fund in association with the Royal College of Obstetricians and Gynaecologists. The study has been known by different names, the Child Health and Education Study (CHES) in 1975 and 1980, Youthscan (1986) and finally the BCS70 (1996 & 2000) as it remains today. Since the original birth study there have been five follow up studies on the full cohort when they were aged 5, 10, 16, 26 and most recently at age 30. Two further studies were carried out on sub samples of the cohort, when they were aged 22 and 42 months but these are not used here. Details of all of the studies can be found in the EDSC documentation (SSRU) and at web addresses (http://www.esds.ac.uk/longitudinal/access/bcs70/, http://www.cls.ioe.ac.uk/).

Originally a health study, the scope and variety of data collected in BCS70 has increased at each follow up to include a wide range of information about the physical, educational, medical and social aspects of the cohort members' lives. Data were collected via a series of questionnaires, interviews and tests completed by parents, school health representatives, head teachers, class teachers and the individuals themselves (table 3.1). Typically for this type of cohort, the aims and requirements of the study have changed over time and in general the amount and depth of information collected has increased at each follow up. The main purposes of each follow up study are described in detail in the BCS70 documentation.

Data from the first four follow up studies (1975, 1980, 1986, 1996) are used in the research presented here (data from the original BBS is used only in examining missing data; data from the 1999/2000[1] follow up were not available for secondary analysis at the outset of this project although it has since become accessible).

3.2 Response rates in BCS70

As with most social surveys loss of study members as the study progresses is inevitable but overall response rates at each BCS70 follow up are good (table 3.1). At each measurement occasion up to age 16 a large proportion of the target sample was achieved. Even in 1996, 26 years after the original study, more than half of the sample were traced. Response rates improved at the most recent follow up in 1999/2000 with responses from 73% of the target sample. The effort required to achieve such an improvement reflects the increasing importance of longitudinal studies in the current social research climate.

In total 18543 (17196 original BBS + 1347 immigrants – see section 3.3.2) individuals took part in BCS70 on at least one occasion but not all of these are included in the research undertaken here. Those born in Northern Ireland were not followed up after the 1970 birth study and so are excluded. Stillbirths, early neo-natal deaths, and those who did not respond to any of the follow up studies were also

[1] For analysis purposes it is assumed that changes in the educational qualifications of study members between ages 26 and 30 would be minimal and so data from the 1999/2000 follow up is not used in the analyses presented in this research.

removed from the sample. Finally cohort members with disabilities (determined from responses at ages 10 and 16) that meant they would not have been exposed to the standard education system were also excluded from the analysis sample.

Table 3.1 : BCS70 follow ups and sources of information 1970-2000

Study	**BBS (1970) Birth**	**CHES (1975) age 5**	**CHES (1980) age 10**	**Youthscan (1986) age 16**	**BCS70 (1996) Age 26**	**BCS70 (1999/ 2000) age 30**
Source	Mother Medical	Parents Tests Medical	Parents School Tests Medical Subject	Parents School Tests Medical Subject	Subject	Subject
Target	17287	16461	16181	15999	15726	15503
*Sample**	16135*	13135	14875	11628	9003	11261
% response	93%	80%	92%	73%	57%	73%

*Achieved sample – at least one survey instrument partially completed.

(http://www.cls.ioe.ac.uk/studies.asp?section=000100020002)

3.3 Missing data in BCS70

One of the first stages in the secondary analysis of sample survey data is the investigation of missing data. Most social surveys have missing data but the amount and impact varies between surveys. Longitudinal surveys are particularly prone to missing data mainly due to non-response (Taris 2000, Laird 1988). In large, complex, longitudinal studies such as BCS70, attrition of the sample over time is (more or less) inevitable particularly when there is a long time between surveys. The amount and sensitivity of data typically collected in national longitudinal studies may also increase the likelihood of non-response as respondents may be unwilling to spend time completing lengthy questionnaires or be unwilling to provide sensitive information.

Missing data can lead to a misrepresentative samples and, if ignored, the value and reliability of results obtained from such a sample may be questionable. The aim of investigating missing data is to determine whether they occur at random throughout the data or whether there are any patterns or similarities in the non-respondents. Where identified, missing data should be dealt with using appropriate methods in order to minimise the possibility of biased results. While investigation of missing data is an essential stage of data analysis, it is not practical to examine responses for every variable in a large data set. The extent of investigation required depends on the research being undertaken, for example in this research missing data on some medical questions would have no effect on subsequent analyses. Usually examination of the key variables under investigation is sufficient. Here missing data on educational and social variables, gender, ethnicity, social class and region are investigated in order to ensure that the population structure remains stable from one follow up to the next and that the changing sample remains representative of the population.

3.3.1 Non-response in BCS70

'Non-response is a fact of life in the field of social survey research' (Elliot 1991) and occurs when, for whatever reason, some of the information requested in the survey is not provided. Definite patterns of non-response have been found in social surveys. In general the most common characteristics of non-respondents are that they are less well educated, from the less skilled social classes, older and living in urban areas (Elliot 1991, McDaniel et al. 1987). There is also a tendency for low response, particularly in education questions from those with no qualifications (Ives 1994). Non response can usually be categorised into three main types: Non-coverage, Unit non-response and Item non-response (Kalton, 1981). Non-coverage occurs when the sampling frame omits some of the population but as BCS70 is a national birth cohort, non-coverage is not a problem.

3.3.2 Unit non-response in BCS70

Unit non-response occurs when information is not collected from a sample unit, i.e. a cohort member, and is a major cause of missing data in BCS70. Reasons for unit non response may include a study member refusing to take part, not being traced or even a lost questionnaire (Nisselson 1983). For the main part unit non-response is due to attrition of the sample over time, i.e. sample members dropping out of the study or being lost between follow ups. There is also some unit non-response in BCS70 due to the addition of immigrants up to 1986 where data for studies prior to the newcomer joining the study are missing. Non respondents are identified at each BCS70 follow up and their social characteristics are examined to determine whether or not the (social) structure of the cohort is distorted by attrition and the addition of immigrants (table 3.2) over time.

3.3.2.1 Addition of immigrants to BCS70

Immigrants added to the original cohort (newcomers) account for (1347 /18543) 7% of the total sample (table 3.2).

Table 3.2 : Trace rates and addition of immigrants to BCS70 cohort

Study year	Sample size**				Total (respondents)
	Entry into study				
	1970	1975	1980	1986	
1970 (Birth)	17196 *(16165)**	-	-	-	16165
1975	12756	**379**	-	-	13135
1980	13715	322	**838**	-	14875
1986	10709	274	515	**130**	11628
1996					9003

* *16165 excluding born in Northern Ireland, stillbirths and neonatal death & ESN*
** *based on total number of respondents at each follow up until 1986*

In general immigrants were evenly divided between the sexes at each follow up and were distributed throughout regions in fairly similar proportions to the original cohort members, with the expected peaks in regions with large cities where employment opportunities are higher (table 3.3, pg 30). Newcomers were more likely to be from an ethnic minority but as the numbers are small the overall ethnic structure of the cohort is virtually unchanged. The distribution of newcomers by social class differs slightly from one study to the next but does not severely impact on the social class distribution of the total sample. Overall as the number of newcomers at each study is small in comparison to the sample size, their addition does not have a major impact on the social structure of the cohort

3.3.2.2 Attrition in BCS70

As with most long term longitudinal studies, the main cause of unit non-response in BCS70 is attrition of the sample over time. This is not unexpected as the time intervals between BCS70 studies are long (between 4 and 10 years). The largest dropout occurred between the birth survey and the 5 year survey when approximately 20% were not traced. Although a further 2% were lost between 1975 and 1980, at the same time many of those who were not traced in 1975 were located at this attempt, resulting in a response from 92% of the original cohort. Between the 1980 and 1986 studies the response rate dropped by a further 19% and between the 1986 and 1996 studies another 16% of the original sample were not traced (table 3.1).

Examination of the distribution of dropouts on key social variables (table 3.4, pg 31) shows that similar proportions of males and females were lost up until 1980 but between 1980 and 1986 a higher proportion of males dropped out leaving males slightly under represented (Despotidou & Shepherd 2000). A higher percentage of ethnic minorities than U.K. origin (white) members dropped out of the study over time but overall the ethnic distribution of respondents does not differ greatly between studies. The overall regional structure of the sample remains stable over time although the dropout rate is slightly higher in the South East region, possibly because the region includes the London area where higher rates of change of address may mean more study members were untraced. There were some fluctuations in dropouts across the different social classes over time (table 3.4), for example a higher percentage of those with parents in the professional class were lost between 1975 and 1980.

The investigation of the newcomers and dropouts does reveal slight trends but the numbers are small and overall the changes in the social structure of the cohort (see appendix 3) are not considered to be large enough to bias the sample. Detailed investigations into dropout in BCS70 draw similar conclusions (Shepherd 1995, ONS 2000) and report minor under representations of certain groups but that overall the study provides a valid sample of the population of Great Britain throughout. Based on these reports and the investigation of missing data here, it is assumed here that unit non response in BCS70 occurs at random.

Table 3.3 : Distribution of immigrants on key explanatory variables

	1970 Original	Numbers (*percentages*)			Total
		1975 additions	1980 additions	1986 Additions	
Gender					
Male	**8357 *(51.8)***	199 *(52.5)*	459 *(54.8)*	64 *(49.2)*	**9079 *(51.9)***
Female	**7804 *(48.1)***	180 *(47.5)*	379 *(45.2)*	66 *(50.8)*	**8429 *(48.1)***
Not known	**2 *(0.0)***	0 *(0.0)*	0 *(0.0)*	0 *(0.0)*	**2 (0.0)**
Ethnic Group*					
U.K/ Irish	**13095 (80.4)**	321 *(84.7)*	497 *(59.3)*	44 *(33.8)*	**14868 (84.9)**
European other	**80 (0.5)**	5 *(1.3)*	19 *(2.3)*	1 *(0.8)*	**104 (0.6)**
West Indian	**164 (1.0)**	4 *(1.1)*	6 *(0.7)*	15 *(11.5)*	**200 (1.1)**
Indian – Pakistani	**311 (1.9)**	20 *(5.3)*	97 *(11.6)*	7 *(5.4)*	
Other Asian	**10 (0.1)**	5 *(1.3)*	5 *(0.6)*	5 *(3.8)*	**424 (2.4)**
African	-	-	-	-	
Other	**53 (0.3)**	5 *(1.3)*	26 *(3.1)*	12 *(9.2)*	**97 (0.6)**
Not stated/known	**2573 (15.8)**	19 *(5.0)*	188 *(22.4)*	46 *(35.3)*	**1817 (10.4)**
Social Class					
I	**780 (4.8)**	42 *(11.1)*	47 *(5.6)*	9 *(6.9)*	**878 (5.0)**
II	**1799 (11.1)**	55 *(14.5)*	129 *(15.4)*	14 *(10.8)*	**1997 *(11.4)***
III NM	**1809 (11.2)**	43 *(11.3)*	64 *(7.6)*	7 *(5.4)*	**1923 *(11.0)***
III M	**7123 (43.9)**	140 *(36.9)*	219 *(26.1)*	8 *(6.2)*	**7490 (42.8)**
IV	**2310 (14.4)**	49 *(12.9)*	76 *(9.1)*	4 *(3.1)*	**2439 (13.9)**
V	**1007 (6.4)**	14 *(3.7)*	30 *(3.6)*	1 *(0.8)*	**1052 *(6.0)***
Other	**476 (2.9)**	1 *(0.3)*	-	4 *(3.1)*	**481 *(2.7)***
Not stated/known	**859 (5.4)**	35 *(9.2)*	273 *(32.6)*	83 *(63.8)*	**1250 *(7.1)***
Region**					
North	**992 *(6.1)***	11 *(2.9)*	28 *(3.3)*	5 *(3.8)*	**1036 *(5.9)***
York & Humberside	**1449 *(9.0)***	93 *(24.5)*	71 *(8.5)*	8 *(6.2)*	**1621 *(9.3)***
North West	**2116 *(13.1)***	36 *(9.5)*	84 *(10.0)*	8 *(6.2)*	**2244 *(12.8)***
East Midlands	**1005 *(6.2)***	13 *(3.4)*	61 *(7.3)*	11 *(8.5)*	**1090 *(6.2)***
West Midlands	**1706 *(10.6)***	41 *(10.8)*	90 *(10.7)*	10 *(7.7)*	**1847 *(10.5)***
East Anglia	**522 *(3.2)***	17 *(4.5)*	15 *(1.8)*	12 *(9.2)*	**566 *(3.2)***
South East	**4913 *(30.4)***	102 *(26.9)*	206 *(24.6)*	41 *(31.5)*	**5262 *(30.1)***
South West	**1022 *(6.3)***	26 *(6.9)*	39 *(4.7)*	9 *(6.9)*	**1096 *(6.3)***
Wales	**859 *(5.3)***	6 *(1.6)*	23 *(2.7)*	5 *(3.8)*	**893 *(5.1)***
Scotland	**1567 *(9.7)***	11 *(2.9)*	84 *(10.0)*	20 *(15.4)*	**1682 *(9.6)***
Overseas	**12 *(0.1)***	23 *(6.1)*	9 *(1.1)*	-	**44 (0.3)**
Not known/missing	**0**	0	128 *(15.3)*	1 *(0.8)*	**129(7.4)**
	16163	**379**	**838**	**130**	**17510**

*Ethnic group was not recorded at 1970 BBS. Figures taken from 1980 follow up
**1970 figure based on mother's region of residence

Table 3.4 : Distribution of dropouts on key explanatory variables

	Numbers *(percentages)*				
	1970 Original	Dropouts by 1975	Dropouts by 1980	Dropouts by 1986	Dropouts by 1996
Sex					
Male	**8357 *(51.8)***	1760 *(51.3)*	546 *(52.2)*	2258 *(56.4)*	2880 *(50.4)*
Female	**7804 *(48.1)***	1670 *(48.7)*	502 *(47.8)*	1744 *(43.6)*	2829 *(49.6)*
Not known	**2 *(0.0)***	1 *(0.0)*	0	0	0
Ethnic Group*					
European U.K	**13095 (80.4)**	*	901 *(86.1)*	3214*(80.3)*	4320*(75.7)*
European other	**80 (0.5)**	*	21 *(2.0)*	36*(0.9)*	14*(0.2)*
West Indian	**164 (1.0)**	*	23 *(2.2)*	72 *(1.8)*	37 *(0.6)*
Indian – Pakistani	**311 (1.9)**	*	44 *(4.2)*	114 *(2.9)*	119 *(1.9)*
Other Asian	**10 (0.1)**	*	3 *(0.3)*	4 *(0.1)*	13 *(0.9)*
African	-	*	5 *(0.5)*	-	-
Other	**53 (0.3)**	*	7 *(0.7)*	28 *(0.7)*	50 *(097)*
Not stated/known	**2573 (15.8)**	*	42 *(4.0)*	534 *(13.3)*	1166 *(39.1)*
Social class					
I	**780 (4.8)**	165 *(4.8)*	81 *(7.7)*	153 *(3.8)*	269 *(4.7)*
II	**1799 (11.1)**	360*(10.5)*	182 *(17.4)*	647*(16.2)*	953*(16.7)*
III NM	**1809 (11.2)**	312 *(9.1)*	72 *(6.9)*	245*(6.1)*	308*(5.4)*
III M	**7123 (43.9)**	1327 *(38.7)*	416 *(39.8)*	1384 *(34.6)*	1226 *(21.5)*
IV	**2310 (14.4)**	463 *(13.5)*	133 *(12.7)*	443 *(11.0)*	290 *(5.1)*
V	**1007 (6.4)**	254 *(7.4)*	61 *(5.8)*	141 *(3.5)*	57 *(1.0)*
Other	**476 (2.9)**	191 *(5.6)*	2 *(0.2)*	0 *(0)*	170 *(2.9)*
Not stated/known	**859 (5.4)**	359 *(10.5)*	99 *(9.5)*	989 *(23.8)*	2436 *(42.7)*
Region					
North	**992 *(6.1)***	151 *(4.4)*	40 *(3.8)*	160 *(4.0)*	338 *(5.9)*
York& Humberside	**1449 *(9.0)***	292 *(8.5)*	83 *(7.9)*	334 *(8.3)*	541 *(9.5)*
North West	**2116 *(13.1)***	401 *(11.7)*	143*(13.7)*	435*(10.9)*	616*(10.8)*
East Midlands	**1005 *(6.2)***	205 *(6.0)*	75 *(7.2)*	197 *(4.9)*	515 *(9.0)*
West Midlands	**1706 *(10.6)***	314 *(9.2)*	113*(10.8)*	387 *(9.6)*	666 *(11.7)*
East Anglia	**522 *(3.2)***	61 *(1.8)*	42 *(4.0)*	58 *(1.4)*	191 *(3.3)*
South East	**4913 *(30.4)***	1294 *(37.8)*	358 *(34.2)*	1073 *(26.8)*	1480 *(25.9)*
South West	**1022 *(6.3)***	166 *(4.8)*	82 *(7.8)*	204 *(5.1)*	533 *(9.3)*
Wales	**859 *(5.3)***	128 *(3.9)*	29 *(2.8)*	120 *(3.0)*	469 *(8.2)*
Scotland	**1567 *(9.7)***	403 *(11.7)*	65 *(6.2)*	345*(8.6)*	335*(5.9)*
Overseas	**12 *(0.1)***	12 *(0.3)*	16*(1.5)*	23 *(0.6)*	
Not known/missing	**0**	0 *(0.0)*	0 *(0.0)*	666 (16.6)	25 (0.4)
	16163	**3431**	**1046**	**4002**	**5709**

* Figures based on those lost from one wave of study to the next. No account taken of those who dropped out but returned to study later.

3.3.3 Item non-response in BCS70

Item non-response is the most commonly encountered type of missing data in social surveys and occurs where a sample member responds to a follow up (or part of) but does not provide all of the information requested. Even with the good response rates in BCS70 there is much item non-response and this is typical of large scale studies where the chance of item non-response is high due to the amount of information requested and the number of questionnaires and interviews used to obtain it. Although a reasonable proportion of those traced responded at each measurement occasion not all respondents completed all of the questionnaires at each study (table 3.5). Response to individual questionnaires at the 1986 follow up was particularly poor in relation to other follow ups.

In general item non-response is more likely in self completion questionnaires than in face to face interviews where the interviewer will aim to maximise completion. Item non-response may occur because the respondent does not know or has forgotten the information requested or they might refuse to answer questions of a personal or sensitive nature (Hair et. al 1995). Invalid responses are also a source of missing data and even when valid responses are collected, lost questionnaires or miscoding of data during transfer to an electronic medium results in item non-response.

As the outcome of interest in this research is educational attainment, missing data on education outcome variables reduces the sample size as these study members cannot be included in subsequent analyses. However even after accounting for this there is still a reasonable sample for analysis at each measurement occasion (table 3.6). Further reduction in sample sizes is inevitable as there will also be item non-response on social background variables (table 3.6), and most statistical analysis packages delete cases with missing values from analysis. An advantage of longitudinal data is that missing values can sometimes be determined from responses to earlier or later questionnaires. Hence reduction of sample sizes due to missing data can be kept to a minimum.

Table 3.5 Response to questionnaires

1975 (age 5)	1980 (age 10)	1986 (age 16)	1996 (age 26)
Maternal Self-completion questionnaire (13135) Home Interview (13135) Test Booklet (13135)	**EDUCATIONAL PACK** Comprehension test (12701) Friendly Maths test (11719) Edinburgh Reading test (11719) British Ability Scales (11719) Educational Score form (12805) Educational questionnaire (12755) Pupil question form (12699) **HEALTH PACK** Maternal Self-completion form (13679) Parental Interview form (13869) Medical Examination form (13869)	**EDUCATIONAL PACK** Student score form (6003) Moving On (4433) Health-related behaviour (5265) Home and all that (6394) Friends & outside world (6290) Life and leisure (6417) Dietary diary (4693) Educational (teacher's) questionnaire (3816) Head teacher questionnaire (4592) **HEALTH PACK** Parental Interview form (9584) Maternal self-completion form (8993) Student self-completion form (6898) Medical Examination form (6143) Leisure and Activity Diary (7544) Family follow up form (7336)	Where are you now? Questionnaire (9003)

Table 3.6: Percentage of item non-response on selected variables

Variable	Age 5	Age 10	Age 16	Age 26
Education Variables	13.6%	25.3%	36.9%*	7.1%
Sex	0%	0%	0%	0%
Region	0%	13.5%	0.4%	-
Social Class	6.6%	17.75	41.4%	-
Ethnic group	0.7%	2.55	1.7%	-
Total achieved sample (N)	13135	14875	11628	9003
Sample for analysis**	11357	11119	7336	8365

* based on respondents to Document T – the family follow up form

** sample sizes based on valid educational data are liable to further reduction due to missing data on explanatory social variables

Initially the aim was to include only those cohort members who had responded at every follow up in subsequent analyses. However, preliminary investigations revealed that there were only 4715 individuals who had done so. Hence in order to maximise sample sizes, all respondents with valid responses on variables relating to educational attainment at each time point are included in the following analyses.

3.4 Methods for dealing with missing data

The methods used for dealing with missing data depend on the amount and type of non-response are present. The ideal solution would be to eliminate missing data from a survey entirely but this is rarely achievable. Probably the simplest approach to analysing a data set containing missing data is to use complete data only. Cases or variables with missing data are deleted from the sample but this is only appropriate if data are missing completely at random (Laird 1988, Rubin 1976) which is rarely the case. In practice it is more common to reduce the amount of missing data or to compensate for it.

In general two main types of compensation procedures are used, weighting and imputation. Although the two are in essence different, they both involve building on the available information to represent missing information. The compensation method used usually depends on the type of non-response being tackled and it is not uncommon for both to be used together. Non coverage and unit non-response are usually compensated for using weighting techniques (Madow & Olkin 1983, Elliot 1991) where adjustments alter the weight of respondents to compensate for non-respondents. The little information available about the units is used to form subgroups that are then weighted to compensate for the non-respondents, and hence all the known information about non-respondents is retained. Although not employed here, weighting for non-response has been used in existing analyses of data from longitudinal studies. For example, Drew & Gray (1990) use weighting to population values in their analyses of data from the Youth Cohort Study (YCS) while Bynner et al. (1996) use composite weighting in their work comparing NCDS and BCS70.

Imputation assigns values to missing responses. It is applicable for item non-response which is the main source of missing data encountered in this research. When item non-response occurs there is often a considerable amount of information about the sample unit available (Rizvi 1983) and this can be used to calculate an imputed value that replaces the missing value. Imputation techniques vary depending on the data available and are described in detail by Heitjan and Landis (1993), Kalton (1982) and Rubin (1987). In general most techniques use a selection of the available data as auxiliary variables in assigning values to missing responses. When used successfully non-response can be greatly reduced using imputation but the effects of any compensation technique should be monitored. In theory imputation could eliminate missing values from survey data but in practice the process can actually introduce significant bias into the data if used incorrectly. In general it is normally accepted that imputation has little effect, in terms of bias, on a whole data set if it is only performed for a small proportion of the data (Kalton 1981).

Other approaches to dealing with non response include model based procedures where missing data is included as a factor in the modelling process (Copas and Li 1997, Little & Rubin 1987). Such methods are not necessary for the missing data in BCS70 and are not used here.

3.5 Imputation in BCS70

Imputation techniques can work very successfully for longitudinal studies as missing information can often be obtained from data collected at a different occasion, either a previous or later follow up. Sometimes this is a straightforward process of substituting a missing response with a valid one, for example gender does not change between BCS70 follow ups and where the information is missing at one occasion it is possible to directly impute the response from another follow up survey. For the most part deductive imputation is used to replace missing values in BCS70, for example on social class and ethnic group variables.

3.5.1 Imputation for ethnic group

An ethnic group classification was derived from all ethnic group variables by replacing missing values at one sweep with valid answers from another. For the majority, ethnic group recorded at age 5 is used as it was the most complete response (ethnic group was not recorded at the birth study). Where the information was missing at age 5, responses at ages 10 and 16 were imputed. The ethnic group classifications used at each occasion differed slightly and so these were combined so that all data was coded using the same ethnic group categories. In general there was little discrepancy between valid ethnic group classifications at the different occasions, i.e. the responses at age 5 matched those at ages 10 and 16 for the most part. Where there was a mismatch, all other variables relating to ethnicity, including country of birth, parents' ethnic group etc. were examined to try and determine a valid classification. In most cases this information was also missing. In total a valid ethnic group classification was deduced for approximately 97 % of those included in the analysis sample.

3.5.2 Imputation for Social Class

Social class (based on the profession of the male head of household) was recorded at each follow up study using the Registrar General's social class groupings. Where social class based on male head of household was missing then social class based on the mother's occupation was substituted where available. In general this resulted in a small reduction in the amount of missing data but the social class distribution of the sample was maintained (Table 3.7)

Table 3.7 Percentage missing data after imputation

Social class based on	1975	1980	1986
Father's SC only	6.6	22.9	41.4
Father's and Mother's SC	4.2	18.2	37.4
Father's, mother's and most recent SC	N/A	6.7	6.9

Where social class was still missing then a response from social class information collected at the previous follow up study was imputed. However this resulted in a distortion of the social class distribution of the sample as the distribution of social class groups at age 16 shows (Table 3.8). The imputation procedure takes no account of social class mobility (Breen & Goldthorpe 2001). Hence this shows that the effects of imputation must be monitored at all stages of the imputation process to ensure that the data remains stable and does not change significantly from the original distribution.

Table 3.8 Percentage social class distribution of sample at age 16 after imputation

	Social class of father/ male head of household	Addition of mother's social class where known	Addition of most recent social class (from age 10 or age 5)
I- Professional	4.5	4.5	6.1
II – managerial	16.6	17.0	21.8
IIINM skilled non manual	5.7	6.3	20.4
IIIM skilled manual	22.4	22.6	25.7
IV - Skilled	5.2	5.7	11.5
V - Semi & non skilled	1.3	1.5	2.7
Other	3.2	4.9	4.9
Missing	41.4	37.4	6.9

For the following analyses imputation is carried out where possible while maintaining the original social structure of the sample. Overall missing data due to item non-response is substantially reduced as a result of imputation. Some collapsing and combining of variables (chapters 4-7) also helped to reduce missing data for the purpose of statistical analysis.

Chapter Four: Exploratory Data analysis

4.1 Introduction to Exploratory Data Analysis

Statistical analysis of data from large social surveys is carried out in two stages, data exploration and confirmatory analysis. Exploratory data analysis (EDA) is an integral part of any analysis and is as much about 'finding the question' as 'seeking the answer' (Everitt & Dunn 2001). EDA provides initial indications of the relationships that exist between investigative factors and the outcome of interest, in this case between social background factors and educational attainment and acts as a guide to defining the subsequent, more complex, analyses that should be carried out. Basic analyses, such as descriptive statistics, graphical analysis, examinations of correlations and distributions of variables are commonly used at the EDA stage. More formal statistical procedures such as factor analysis techniques can also be used, particularly when dealing with large multivariate data sets. Once hypotheses have been established the second stage, confirmatory analysis, which usually involves some form of statistical modelling and associated statistical significance testing can be carried out.

This chapter details exploratory analysis of the educational and social data within BCS70. The main objectives of EDA here are to gain some understanding of the relationships between social background factors and educational attainment at each follow up occasion and to determine which, if any, social factors can be reliably measured and monitored over time in order to study development of the effects of background factors on attainment. For the most part associations between attainment and social background factors are investigated by comparing standardised mean scores using t-tests and ANOVA techniques bearing in mind that findings may be affected by the large sample size (section 2.5). Principal components analysis is also used in deriving overall educational attainment scores. EDA also highlights some of the problems that can arise in statistical modelling of survey data and in the use of longitudinal social survey data - for example, determining which information to include in subsequent analyses and defining reliable estimates of overall educational attainment and social background. Such issues, as they apply to BCS70, are also discussed in this chapter.

4.2 Measurements of Educational Attainment in BCS70

Like many national longitudinal studies, BCS70 was not designed with any specific analyses in mind, other than to provide a general record of various aspects of the study member's life at each measurement occasion. Several measures of educational attainment were recorded at each follow up study. The timings of the first three follow ups studies coincide approximately with significant points in the education system, at age 5 when children were just starting school, at age 10 when they were nearing the end of primary education and at age 16 when they were nearing the end of compulsory education. At the fourth and fifth follow ups when the cohort members were aged 26 and 30 respectively, most study members would have completed their formal education.

At age 5 a series of four cognitive tests were completed as part of the home interview and at age 10, attainment was recorded on the school questionnaire using three separate tests (table 4.1). At age 16 there were several questions relating to attainment on the teachers' questionnaire but response to the questionnaire was poor. A more complete record of attainment at 16 was collected on the family follow up form which was carried out approximately six months after the main 1986 study and collected full details, including results, of all public examinations taken. At the 1996 follow up study, when the cohort members were aged 26, a single questionnaire was used to collect data and members were asked to provide details of all academic and vocational qualifications achieved to date. At the most recent follow up in 1999/2000[1] data were collected by interview and a self completion questionnaire that included a section on lifelong learning where details of educational qualifications were requested.

Table 4.1 : Education data collected in BCS70

1975 (age 5)	Copying Designs Test (COPY) English Picture Vocabulary test (EPVT) Human Profile drawing test (PROFILE) Schnoell Reading test (SCHNOELL)
1980 (age 10)	Friendly Maths test (MATHS) Edinburgh Reading test (READING) BAS word similarities test (BAS)
1986 (age 16)	Results of public examinations (GCE O level, CSE)
1996 (age 26)	Retrospective details of all qualifications on self completion questionnaire
2000 (age 30)	Retrospective details of all qualifications on self completion questionnaire

When several measures of attainment from a series of educational tests are available at each occasion a common approach is to calculate overall scores but defining an overall measure of educational attainment can be problematic. In practice definitions vary between research studies depending on the research focus and the availability of data (Yang & Woodhouse 2001, Feinstein 1998, Bynner & Steedman 1995, Fogelman 1984). Alternatively distinct aspects of education may be examined, for example

[1] Data from the 1999/2000 study are not used here as they were unavailable at the outset and for much of the duration of this research. It is assumed that, in general, educational attainments of cohort members would remain the same between ages 26 and 30.

attainment in mathematics and reading are often considered separately (Feinstein & Symons 1999, Brandsma and Knuver 1989, Goldstein 1979).

In this research several different educational outcomes are examined. For exploratory data analysis in this chapter overall scores are computed at ages 5, 10 and 16 in order to investigate general social patterns in educational attainment. Then attainment in mathematics and in English is examined separately in chapter 5 where progress in each subject is examined using multilevel modelling. In chapter 6 the overall scores from preliminary investigations are examined again but are converted to categorical outcomes that can be compared with the highest level of attainment achieved by age 26 (chapter 7).

At ages 5 and 10 an overall attainment score is calculated from the scores achieved in the separate education tests used. The simplest approach to calculating an overall score would be to take the average of the tests at each measurement occasion but this is not always the best approach. In general a more reliable method is to employ some form of statistical data reduction technique that will reduce several scores down to one single overall score.

Principal Components Analysis (PCA) is an appropriate method of data reduction that has been used to derive overall education scores in previous research (Feinstein 1998, Everitt & Dunn 2001). It is appropriate when there is no distinction between dependent and explanatory variables (Chatfield & Collins 1980). Essentially the analysis transforms the data from a set of correlated variables into a set of uncorrelated variables or 'components' with a decreasing order of importance. Hence the original variables should be correlated. The objective is to see if the first few components (or linear combinations) of the analysis account for most of the variation in the data. An eigenvalue is computed for each new component and where this is greater than 1, then the component is considered to be significant (for a more detailed explanation of PCA see Manly 2005, Chatfield & Collins 1980). PCA is used to derive overall attainment scores at ages 5 and 10.

4.2.1 Overall Attainment at age 5

At age 5 the majority of respondents (94%) completed three of the four educational tests used (COPY, EPVT, PROFILE) but completion rates for the Schonell reading test were poor and so it is not used in subsequent analyses. The range of scores on the three remaining tests vary greatly (0-54, 0-16 and 0-8 in EPVT, PROFILE and COPY tests respectively) and so taking the average is not an appropriate method of calculating an overall score. Correlations between the three scores do not indicate strong linear associations (table 4.2) but they are significant (graphical analysis did not yield any clearer understanding), and so on this basis PCA is applied to the three test scores in order to derive a summary measure of attainment.

Table 4.2 Correlations between test scores at age 5

	TEST *(scoring range)*		
	EPVT *(0-54)*	PROFILE *(0-16)*	COPY *(0-8)*
EPVT	1.000		
PROFILE	.194*	1.000	
COPY	.315*	.190*	1.000

* significant at 0.01% level

The results of PCA on test scores at age 5 are shown in table 4.3. Only the first component is significant ($\lambda = 1.462$) and the associated component matrix (table 4.3) gives the proportions that each of the three original scores contribute to the new PCA score.

Table 4.3 : PCA for cognitive tests at age 5

	Initial eigenvalues	% variance explained	Cumulative Variance	**Component Matrix**		
				EPVT	Profile	Copy
Component 1	1.462	48.7	48.7	0.735	0.616	0.736
Component 2	0.838	28.0	76.7			
Component 3	0.700	23.3	100			

Overall attainment score at age 5 is calculated as

PCAscore (age 5) = (0.735* EPVT)+(0.616*PROFILE)+(0.736*COPY)

When compared, the average of the three test scores and the derived PCA score show almost perfect correlation (.999) so in this instance PCA analysis does not necessarily provide a better overall measure than the average. Either measure would yield the same analysis results. In subsequent analyses overall scores are calculated using the PCA method in order to be consistent with the measures calculated at age 10 (see next section).

4.2.2 Overall Attainment at age 10

At age 10 correlations between the three measures of attainment (READ, MATHS, BAS) are much higher than at age 5 and indicate strong linear relationships between the test scores (table 4.4)

Table 4.4 Correlations between test scores at age 10

	AGE 10 *(scoring range)*		
	READ *(0-54)*	MATHS *(0-72)*	BAS *(0-20)*
READ	1.000		
MATHS	.716*	1.000	
BAS	.583*	.575*	1.000

* significant at 0.01% level

PCA is applied to the raw test scores to create an overall measure of attainment (table 4.5) Again only the first component is significant (λ= 2.254) but in this case more than 75% of the total variation is explained, a much more satisfactory proportion than at age 5. The associated component matrix (table 4.5) gives the proportions of each distinct original score that contribute to the new PCA score.

Table 4.5: PCA for test scores at age 10

	Initial eigenvalues	% variance explained	Cumulative Variance	**Component Matrix** EPVT	Profile	Copy
Component 1	2.254	75.13	75.13	0.887	0.890	0.821
Component 2	0.456	15.49	90.62			
Component 3	0.281	9.38	100.0			

Overall attainment score at age 10 is calculated as

PCAscore (age10) = (0.887* READ)+(0.890*MATHS)+(0.821*BAS)

When compared, mean scores in MATHS and READING are highly correlated with the derived PCA score (0.929 and 0.919 respectively) and average BAS score is strongly correlated with the PCA score (0.685), but the three do not carry equal weights. Here PCA provides a better overall estimate than the average of the three separate scores and is used in subsequent analyses.

4.2.3 Overall Attainment at age 16

At the third follow-up study in 1986 assessments of several aspects of academic attainment were requested on the teachers' questionnaires as the cohort members, then aged 16, would still have been in compulsory full time education. However, response to this questionnaire was low and the information is only available for approximately one third of the achieved sample (3816 / 11628 individuals). A supplementary questionnaire, the family follow up form was issued to all BCS70 members about six months after the main study and this requested details of all public examinations taken, including type of exam, subject and grade achieved. Response to this survey was considerably higher (7336) and it provides a much more complete source of educational attainment measures for the cohort at age 16.

An overall score is calculated from the results of public examinations i.e. O level and CSE grades, based on a commonly used point system (Yang & Woodhouse 2001) shown in table 4.6.

Table 4.6 Point scores allocated to examination grades

Grade achieved	Points
GCE O level grade A	7
GCE O level grade B	6
GCE O level grade C or CSE grade 1	5
GCE O level grade D or CSE grade 2	4
GCE O level grade E or CSE grade 3	3
CSE grade 4	2
CSE grade 5	1

The score is calculated as

$$\Sigma[(\text{no.of GCE grade A} * 7) + (\text{no.of GCE grade B} * 6) + (\text{no.of GCE grade C} * 5) + (\text{no.of GCE grade D} * 4) + (\text{no.of GCE grade E} * 3) + (\text{no.of CSE grade 1} * 5) + (\text{no.of CSE grade 2} * 4) + (\text{no.of CSE grade 3} * 3) + (\text{no.of CSE grade 4} * 2) + (\text{no.of CSE grade 5} * 1)]$$

For cohort members in England and Wales this score is based on GCE O level and CSE examinations as these were still in use in 1986 (public examinations taken after 1986 are not taken into consideration at this point). In Scotland, the standard grade system equivalent to GCSE was already in place in 1986 (The Scottish Office 1996) and so for cohort members in Scotland the total score is based on results achieved in Scottish O level and standard examinations. Finally, as the tests used at each follow up were appropriate to age and expected ability it is assumed that the overall scores derived from the raw data at ages 5, 10 and 16 can be compared over time.

4.2.4 Attainment at age 26

At the 1996 follow up study, when the cohort members were aged 26, a single questionnaire was used to collect data. Cohort members were asked to provide details of all academic and vocational qualifications achieved to date. For analysis purposes it is assumed that formal education would have been completed at this time and so a "highest level of academic attainment" variable is derived for each study member (table 4.7).

Table 4.7 Distribution of attainment at age 26

Highest educational qualifications achieved	% of respondents
No qualifications	5.7
1-4 GCE O level passes A-C *Includes, GCE O level A-C, CSE grade 1, GCSE A-C Scottish O levels A-C, Scottish standard grades A-C)*	49.4
5 or more than 5 GCE O level passes grade A-C *Includes, GCE O level A-C, CSE grade 1, GCSE A-C Scottish O grades A-C, Scottish standard grades A-C)*	9.0
At least 1 A level pass or HE certificate *Includes HND, HNC Dip. etc.*	15.1
First degree	15.5
Post graduate qualification	5.1
n	8359

4.3 EDA of social background influences on attainment

The aim here is to examine the socio-economic factors that have the most effect on attainment and to observe how the effects change and develop over time. At each BCS70 follow up information was collected about many aspects of the study members' lives that could potentially affect attainment. To include all of the available information, though ideal, would be impractical in terms of statistical modelling and probably unnecessary as much of the information will ultimately be found to have little impact on attainment (section 4.4). EDA helps to determine what social background information is available at each follow up study, and what can be monitored over time and hence included in subsequent statistical modelling of the data here. It also helps to eliminate redundant explanatory variables from further analysis. The main explanatory variables (raw and derived) available at each follow up are detailed in table 4.8 (detailed descriptions of social background variables are given in appendix 4).

As most of the social background variables in BCS70 are categorical, EDA of the associations between these factors and attainment is carried out by comparing mean overall attainment scores between categories of social variables using independent sample t tests and ANOVA techniques (n.b. sample sizes fluctuate due to missing responses on social factors). Associations between social background factors and attainment are compared at each measurement occasion which provides an initial impression of how the associations change over the course of compulsory education. Overall scores are standardised so that they can be compared directly between occasions, hence aiding interpretation of associations between social factors and attainment over time.

Table 4.8 Explanatory variables (raw and derived) in BCS70 follow up studies

1975 age 5	1980 age 10	1986 age 16	1996 age 26
Sex	Sex	Sex	Sex
Ethnic Group	Ethnic Group	Ethnic Group	Ethnic Group
Social Class	Social Class	Social Class	Social Class
Parents' qualifications	Parents' qualifications	Parents' qualifications	
Region	Region	Region	
Tenure of accommodation.	Tenure of accommodation	Tenure of accommodation	
Overcrowding	Overcrowding	Overcrowding	
Number of children in family	Number of children in family	Number of children in family	
Position in family	-	Position in family	
Child has been in care	Child has been in care	Child has been in care	
Neighbourhood	Neighbourhood	Area	
Attended pre-school	-	-	
	Income	Income	
	Family received benefits	Family received benefits	Age left FT education
	Free School meals		
	School mixed or single sex		

4.3.1 Gender

The educational attainments of males and females are investigated by comparing standardised mean scores at each measurement occasion. The results (table 4.9) suggest that there is already a difference in average performance between the sexes at the very earliest stages of education with boys achieving slightly higher test scores on average than girls. Towards the end of primary education, (age 10) the attainment gap has all but disappeared with similar average attainment for both boys and girls. By the end of compulsory education (age 16) there is no evidence of a difference in the average attainment of boys and girls as they achieve similar scores in O level (and equivalent) examinations. Throughout girls achieve slightly lower scores on average.

Table 4.9 : Standardised mean overall scores at ages 5, 10 and 16 by gender

	Male	Female	Difference	95% CI for difference
Age5 Mean score *N*	 0.102 *(5835)*	 -0.108 *(5522)*	0.210	0.173, 0.246*
Age 10 Mean score *N*	 0.011 *(5666)*	 -0.011 *(5453)*	0.022	-0.015, 0.06
Age 16 Mean score *N*	 0.014 *(3314)*	 -0.012 *(3794)*	0.026	-0.198, 0.073

* significant at α=5%

By adulthood (age 26) the situation has changed again with a larger proportion of males than females having reached the highest attainment levels. Attainment levels can be split into two sections, those who stayed on after the O level stage, i.e. the end of compulsory education, and those who did not. Similar proportions of males and females stayed in education after age 16 (36.4% of males and 35.2% of females) and of those males are more likely than females to have achieved a degree or post graduate qualification (22.4% and 19.1% respectively) (table 4.10). Males and females who left the education system at age 16 were fairly equally distributed across the lower attainment categories.

Table 4.10 Percentage distribution of attainment at age 26 by gender

	N	Highest level of Qualification					
		No quals	1-4 GCE 'O' A-C	5 + GCE 'O' A-C	A level & HE cert	Degree	Post Grad.
Male	*3779*	6.5	48.5	8.5	14.0	17.0	5.4
Female	*4580*	5.1	50.2	9.4	16.1	14.3	4.8
Total	*8359*	5.7	49.4	9.0	15.1	15.5	5.1

4.3.2 Ethnicity

There is marked variation in mean test scores between the various ethnic groups. Throughout compulsory education the U.K. group (referred to from here on as white) are the most educationally successful with higher average scores at ages 5, 10 and 16 than other ethnic groups (table 4.11). However comparison of standardised test scores over time suggests that this advantage decreases as students progress through compulsory education with the ethnic minorities generally 'closing the gap' overall at each successive measurement occasion (table 4.11). After compulsory education an interesting trend emerges with the Asian group, who were the poorest performers at age 5, being much more successful in post compulsory education than the white group.

Table 4.11 Mean standardised scores at ages 5, 10 and 16 by ethnic group

	Age 5		Age 10		Age 16	
	Mean	*N*	Mean	*N*	Mean	N
U.K.(white)	.03	*10978*	.03	*10551*	.34	6796
Non U.K.						
European other	-.47	*48*	-.14	*52*	.22	27
West Indian	-.73	*130*	-.81	*126*	-.35	48
Asian	-1.34	*116*	-.58	*170*	.14	152
Other	-.54	*32*	-.12	*25*	.77	31
Total non U.K.	-0.89	*326*	-0.57	*373*	0.13	258
Total	.00	*11304*	.01	*10924*	.00	7054

By age 26 over 50% of Asians had attained qualifications higher than O levels compared to 36% of the white group (table 4.12) which might suggest that Asians are more likely to progress to, and succeed in post compulsory education than whites and other minority groups. At first this may seem to contradict the common perception that children from the ethnic minorities are less educationally successful than white children. In fact, these findings concur with existing research where it is reported that Asian students make more educational progress, particularly during secondary education, than white and other ethnic minority students (Haque & Bell 2001, McNiece et al. 2004). The figures also suggest that children of West Indian origin are less educationally successful than any other ethnic group during primary and secondary education which agrees with research carried out around the same time as the BCS70 study (Drew & Gray 1990, 1991, Brewer & Haslum 1986, Swann 1985). Here it can be seen that the trend carries on through to tertiary education (table 4.12).

Table 4.12 Percentage distribution of attainment at age 26 by ethnic group

		Highest level of Qualification					
	N	No quals.	1-4 GCE 'O' A-C	5 + GCE 'O' A-C	A level & HE cert	Degree	Post Grad.
U.K.(white)	*7597*	5.1	49.8	9.2	15.4	15.2	5.1
Non U.K							
European other	*43*	9.3	55.8	4.7	11.6	14.0	4.7
West Indian	*64*	3.1	60.9	7.8	17.2	10.9	0.0
Asian	*136*	5.1	36.0	4.4	15.4	27.9	11.0
Other	*34*	0.0	26.5	5.9	14.7	44.1	8.8
Total non U.K.	*277*	4.7	43.7	5.4	15.2	23.8	7.2
Total	*7874*	*5.1*	*49.6*	*9.1*	*15.3*	*15.5*	*5.2*

However, the BCS70 has only a very small proportion of ethnic minorities (approximately 3%) and the numbers in each category are very small. To include all five ethnic groupings in subsequent statistical modelling is infeasible and would lead to problems in model fitting. Where ethnic group is used as a factor in further analyses, classifications are collapsed to two groups, white and non white. Overall the white group achieve higher overall scores at ages 5 and 10 but at age 16 the ethnic minority disadvantage has disappeared (table 4.11). A higher proportion of the non white group stayed in education after age 16 and those who did were more likely to achieve at least a first degree (table 4.12).

4.3.3 Parental qualifications

Past research has shown parental influence and particularly parents' qualifications to be strongly associated with childrens' attainment (Bynner & Joshi 2002, Gayle et al. 2002, Burnhill et al. 1990). The children of parents who have continued beyond compulsory education into third level education are more likely to take a similar education route than children whose parents have no academic qualifications. Information about parents' educational qualifications is well documented at each BCS70 follow up study and preliminary investigations support existing research. Children whose parents have achieved the higher educational attainment levels, particularly a degree, achieve higher test scores on average. The association is evident even at the earliest stages of education, at age 5 and continues through compulsory education (table 4.13) with mean scores at each time point increasing with increasing levels of parental education. This might suggest that children have a definite educational advantage if their parents are educated to degree level.

Table 4.13 Mean standardised scores at ages 5, 10 and 16 by parents' education

Parents' Education	Age 5		Age 10		Age 16	
	Mean	*N*	Mean	*N*	Mean	*N*
No qualifications	-.33	*4280*	-.32	*3921*	-.11	*1663*
Vocational quals.	-.02	*1479*	-.09	*2200*	.06	*907*
O levels	.13	*2398*	.20	*1596*	.36	*1368*
A levels	.28	*894*	.32	*902*	.51	*638*
HE diploma / cert.	.31	*390*	.50	*315*	.28	*232*
Degree or PG qual.	.49	*1582*	.78	*1166*	1.16	*1538*
Total	.00	*11023*	.02	*10100*	.40	*6346*

The trend appears to continue in post compulsory education as there is still a strong association between parents' education and the highest level of educational attainment achieved by the end of the educational career (at age 26). For example, only about 19% of children of parents who had no formal qualifications continued in education and gained qualifications after age 16 compared to 70% of children whose parents were educated to at least degree level (table 4.14).

Table 4.14 Percentage distribution of attainment at age 26 by parents' education

Parents' qualifications	*N*	Highest level of Qualification					
		No quals.	1-4 GCE 'O' A-C	5 + GCE 'O' A-C	A level & HE cert	Degree	Post Grad.
No qualifications	*2287*	10.2	62.6	8.2	11.5	5.5	1.8
Voc. Quals	*1255*	4.5	61.0	9.8	13.9	7.7	2.9
O levels	*1551*	2.5	50.9	10.4	16.4	15.6	3.9
A levels	*719*	2.5	41.6	11.5	17.8	19.6	7.0
HE diploma / cert.	*251*	2.8	41.0	10.0	23.9	19.1	3.2
Degree or PG qual.	*1467*	0.7	21.3	7.7	18.5	37.5	14.3
Total	*7530*	4.8	49.2	9.2	15.3	16.0	5.4

4.3.4 Social Class

Social class inequalities in educational attainment are well documented and the BCS70 data mirrors such inequalities with higher attainment amongst the more advantaged social classes and poorer attainment amongst the less advantaged classes throughout the duration of the study (table 4.15). The difference in attainment between classes already exists at the start of primary education when the children are aged 5, which supports theories that social background and experiences during the formative, pre-school years have an important effect on early learning (Gillborn & Mirza 2000, Feinstein 1998, Bondi 1991, Blatchford et al. 1985). Differences in average scores appear to increase between each follow up study, particularly between ages 10 and 16 where the more advantaged classes (I - professional and II managerial) obtain much higher scores on average.

Table 4.15 Mean standardised scores at ages 5, 10 and 16 by social class

	Age 5		Age 10		Age 16	
Social Class	Mean	*N*	Mean	*N*	Mean	*N*
I (professional)	.56	*769*	.77	*548*	1.30	*504*
II (managerial)	.32	*2196*	.41	*2332*	.78	*1897*
IIINM (skilled non-manual)	.15	*1016*	.24	*1060*	.31	*701*
IIIM (skilled manual)	-.09	*5000*	-.16	*4230*	.05	*2514*
IV (semi-skilled)	-.25	*1415*	-.29	*1357*	-.06	*637*
V(unskilled)	-.57	*514*	-.58	*425*	-.19	*172*
Total	.02	*10910*	.03	*9952*	.38	*6425*

At age 26 (table 4.16) there is still marked diversity in the educational attainment of the different social class groups with those from the more advantaged classes being much more likely to continue and achieve qualifications (74.4% of professional, 51.3% of managerial and 42.2% of skilled non manual compared to 24%, 21.85 and 15.4% of skilled manual, semi-skilled and unskilled respectively) and achieve qualifications beyond compulsory education and into third level education. The professional class (I) were also much more likely to have obtained a degree or higher qualification (56%) than other social class groups (5.0% to 32.2%). Overall preliminary investigations suggest that, if anything, the social class effect increases rather than decreases during compulsory education but this could be subject to unknown influences confounded within social class, hence the need for statistical modelling of the data.

Table 4.16 Percentage distribution of attainment at age 26 by social class

Social class	*N*	Highest level of Qualification					
		No quals.	1-4 GCE 'O' A-C	5 + GCE 'O' A-C	A level & HE cert	Degree	Post Grad.
I	*586*	0.2	17.4	7.8	18.3	39.9	16.2
II	*2064*	1.5	37.2	10.0	19.1	24.7	7.5
IIINM	*836*	3.0	44.6	10.2	18.9	18.2	5.1
IIIM	*3141*	6.9	59.5	9.5	12.8	8.2	3.0
IV	*870*	8.3	62.3	7.6	13.1	6.6	2.1
V	*222*	16.2	64.6	4.1	10.4	4.1	0.9
Total	*7719*	4.9	49.2	9.2	15.5	15.8	15.3

4.3.5 Other social background measures

Other aspects of social background and experiences are often considered in the investigation of educational social inequality. Commonly used indicators of social background include tenure of accommodation, low income and family circumstances (Joshi et al. 1999, Sammons 1995). Several such social background measures are available or can be derived (see appendix 4) in BCS70 (table 4.17) and most are collapsed to two categories. Differences between categories are examined using t tests and for the main part the associations between social factors and attainment reflect existing research findings.

Children from owner occupied homes tend to achieve higher scores on average than those from families in rented or council accommodation (table 4.17). Similarly children from low income families, those receiving benefits and/or free school meals and those who have spent time in care also tend to be low achievers. Other measures such as coming from a large or overcrowded family and being one of the younger children in large families have also been associated with low educational attainment. The preliminary analysis of BCS70 data indicate that children from large and overcrowded families are lower achievers on average than those from smaller families but at age 16 the effect has disappeared and in fact children from large families actually do better on average. Although these trends at age 16 are not reported elsewhere, they should be interpreted with caution as they are based on questions with low response rates which could potentially bias the results. Further investigation is necessary.

Table 4.17 Mean attainment scores at ages 5, 10 and 16 by social background factors

	Age 5		Age 10		Age 16	
	Mean	*N*	Mean	*N*	Mean	N
Tenure						
Owned	0.20	*6541*	0.238	*6332*	0.128	*5099*
Council / rented	-0.31	*4219*	-0.376	*3567*	-0.449	*1292*
95% CI for diff.	(-0.545, -0.470)*		(-0.653, -0.575)*		(-0.637, -0.518)*	
Low income						
Yes			-0.327	*2312*	-0.315	2116
No	*Not recorded*		0.085	*8807*	0.134	4992
95% CI for diff.			(0.360 , 0. 458)*		(-0.499, -0.399)*	
Benefits						
Yes			-0.295	*1684*	-0.238	*613*
No	*Not recorded*		0.53	*9435*	0.023	*6495*
95% CI for diff.			(0.296, 0.399)*		(-0.344, -0.178)*	
Free school meals						
Yes			-.456	*1530*		
No	*Not recorded*		.073	*9589*	*Not recorded*	
95% CI for diff.			(-0.582, -0.475)*			
In care						
Yes	-0.419	*211*	-.436	*158*	-0.379	*189*
No	0.006	*8886*	0.075	*10001*	0.010	*6919*
95% CI for diff.	(0.289, 0.560)*		(-0.616, -0.305)*		(-0.534, -0.245)*	
Overcrowding						
Yes	-0.771	*11075*	-0.304	*275*	0.403	1147
No	0.009	*132*	0.028	*9893*	0.084	2598
95% CI for diff	(-0.610, -0.952)*		(-0. 451, -0.214)*		(0.246, 0.392)*	
Family size						
1-4 children	0.074	*9611*	0.049	*9702*	-0.207	2988
> 4 children	-0.601	*645*	-0.562	*514*	0.261	221
95% CI for diff.	(0.598, 0.753)*		(0.523, 0.697)*		(-0.612, -0.324)*	

4.3.6 Regions

Comparison of average attainment scores across regions shows some variation but there are no marked patterns between regions or over time (table 4.18). Students in Scotland and Southern regions seem slightly more likely to gain higher than average attainment but the differences are small. Regional differences could also be affected by social class composition within the regions which may have an impact on mean attainment. For example, Southern regions have higher proportions of white collar workers and hence one would expect this to be reflected in higher average attainment of children living in these regions. A more informative measure might be to consider the type of area a child lives in. Preliminary analyses suggest that children from traditionally well to do areas, typically suburban towns and more rural locations, achieve higher scores than those from inner city areas during primary education (table 4.19). However by the end of compulsory education at age 16, children in the cities achieved similar scores to those in villages and rural locations and slightly higher scores than those in more suburban towns. Differences in attainment in urban and rural areas are not widely documented in existing research and it is not really possible to carry out any real comparison of urban-rural differences in BCS70 due to the different coding frames used at the different follow up studies (see table 4.19). At best the findings suggest that this is an area worthy of further and more in depth investigation beyond the scope of the research undertaken here.

Table 4.18 Mean standardised scores at ages 5, 10 and 16 by region

	Age 5	Age 10	Age 16
North West	.00	.02	-.04
North	-.05	-.06	-.05
York & Humberside	-.10	-.10	-.09
West Midlands	-.03	-.18	-.13
East Anglia	-.09	.11	-.04
South East	.00	.05	.08
South West	.12	.08	-.01
East Midlands	.09	-.03	-.19
Wales	-.11	.00	.01
Scotland	-.03	.12	.26
Overseas	.06	.26	-
N	12632	12329	7090

* significantly different from 0 (α=0.05)

Table 4.19 Mean standardised scores at ages 5, 10 and 16 by Neighbourhood / Area

	Neighbourhood Description	Mean	*N*
Age 5	Poor	-0.489	*784*
	Average	-0.127	*5464*
	Well to do	0.309	*2642*
	Rural	0.133	2102
Age 10	Inner city	-0.366	*3513*
	Towns/ suburbs	0.256	*4364*
	Rural	0.196	*2041*
Age 16	Big city	0.239	*502*
	Town	0.085	*2112*
	Village	0.226	*1161*
	The country	0.308	255

4.3.7 School Factors

There is little information about the schools attended by the BCS70 cohort members. This is partly due to the fact that detailed information about schools was not requested at the earlier 1975 and 1980 follow up studies. Although detailed information about schools was requested on the teachers' questionnaire at the 1986 follow up, response rates were low as the timing of the study coincided with teacher's industrial action (Feinstein 1998). What little information was collected has only recently (August 2005) been coded and made available and was not available for secondary analysis at the time when this research was carried out. EDA of the few school measures that were available indicate that attending some form of pre-school has a positive effect an attainment with those who had attended pre-school achieving higher overall scores at age 5 (table 4.20). At age 10 type of school appears to have an affect with students attending independent schools scoring significantly higher scores on average than students in any other type of school. Students attending single sex schools also achieved higher scores than those at mixed schools. However, it is likely that the two factors are inter-linked as single sex schools also tend to be independent.

Table 4.20 Mean attainment at ages 5 and 10 by school factors

School factor		Mean *(N)*	Diff	95% CI for diff.
Age 5				
Pre-school	No	-0.251 (1529)	-0.398	-0.453, -0.343*
	Yes	0.147 (5108)		
Age 10				
School Sex (1980)	Mixed	0.716 (9574)	0.729	0. 586, 0.872*
	Single	-0.013 (187)		
School type (1980)	Maintained	-0.054 (7802)		
	Voluntary controlled	0.076 (968)		
	Voluntary aided	0.110 (1347)		
	Direct grant	0.176 (98)		
	Independent	0.945 (256)		
	Other	0.009 (23)		

4.4 Discussion of EDA

The exploratory analysis of BCS70 data highlights important issues that arise in using data from longitudinal studies for investigating trends in educational attainment. Probably the biggest of these is how best to measure attainment from the information available. The various test scores recorded at each follow up study are not easily comparable from one occasion to the next and so an overall score derived from the separate tests is probably the best estimate to use in this case. The derived total score from grades achieved at O levels assumes equal differences between grades. Although this might not actually be the case, there is no obvious better method for estimating attainment at age 16 here and calculating an overall score is common practice. Here where the term compulsory education is used, this means education up to the age of 16 and there is a distinct difference between the types of attainment outcomes for compulsory and post compulsory education which again means that direct comparison of attainment can be a problem.

Defining social background can also be a problem although consistency in social background variables between follow ups is better than for education data. EDA provides initial indications of which social variables are most strongly associated with attainment and hence should be included in further analyses. Most of the social background variables investigated are significantly (see section 2.5) associated with attainment but to include all of these in statistical modelling would be impractical. While it is important to include all important effects in the modelling process some consideration should also be given to the problems associated with multicollinearlity and endogeneity. Models that are contain too many explanatory factors can be cumbersome and problems in model fitting may ensue. As the number of explanatory factors and hence parameter estimates in a model increases interpretation of the results also becomes increasingly difficult. In practice a carefully selected subset of the available data is usually included in modelling, keeping the amount of data to be analysed to a minimum while retaining all important effects. Furthermore, inclusion of all possible explanatory variables here would result in a dramatic decrease in sample size. To this end, maintaining a representative sample and maximising sample size takes priority over inclusion of low response variables that have little impact on the overall outcome.

Many social variables are symptomatic of the different social class groups and so it is unnecessary to include all of them in the modelling process. Formal processes such Principal Components Analysis can be used to reduce the number of explanatory variables in an analysis but this usually leads to derived components that are not easily interpretable (Plewis 1997, Johnson & Wichern 1992). In this research interpretation of the effects of social factors on attainment is of interest and so PCA is not used to reduce the explanatory variables. Collapsing variables by combining like groups into one category is common in social surveys and makes model fitting and interpretation of data easier. The process can also help in selecting a subset of variables for analysis as those that can be collapsed without losing important information are attractive for statistical modelling purposes

In selecting the set of explanatory variables for subsequent statistical modelling consideration is given to the evidence that already exists. Research in the area almost invariably includes gender, ethnic group and social class as explanatory factors in the modelling process. These factors are retained in the following analyses of BCS70 data.

Existing research has shown that even when class differences are controlled disadvantage factors still have an impact on educational attainment, for example low income (Sammons 1995). Ideally other social factors that seem to have an effect over and above that explained by social class should be included in the analysis process. For example EDA here and existing research indicates that parents' educational attainment is an important contributory factor in lifelong educational attainment (Bynner & Joshi 2002, Gayle et al. 2002, Burnhill et al. 1990) and so parents' education is included in subsequent modelling of BCS70 data. It is also worth noting here that all of the factors considered in table 4.17 seem to have a statistically significant effect on attainment although much of this may be due to the large overall sample sizes rather than practical significance and so the results should be interpreted with caution. Some of the measures are based on low responses and not all measures are available at each follow up. The advantage of longitudinal data is that overall summary measures can be deduced by drawing on data from responses to all follow up studies (see appendix 6). An additional measure of 'social disadvantage' is derived from variables relating to low income, benefits and free school meals and similarly a large family indicator based on overcrowding and family size variables is also derived. The benefits of creating such summary measures is that several highly correlated social background variables are reduced to just one or two variables for the modelling process. At the same time maximum sample size is maintained by reducing the opportunity of individuals being excluded from analysis due to missing data.

Having considered these obstacles the results of exploratory analysis show that the dataset as a whole provides a reliable and representative data source for investigations into social effects on educational attainment during the 1970s, 1980s and 1990s. In general the findings reflect existing research and also raise some interesting points. For example examination of attainment among the different ethnic groups reveals long term trends that may not always have been reported in the past. Also the strong association between parents' education and attainment throughout the education system from as early as age 5 might suggest that social background and family influences have a greater impact on attainment than influences from within the education system itself. The findings also suggest that social class inequalities in attainment did not change throughout the duration of the study which would suggest that initiatives aimed at providing equal educational standards and opportunities for all sections of society did not have the desired impact.

Another important issue raised by the EDA exercise is that the BCS70 is lacking in information relating to the schools attended by the study members. Factors from within the school environment such as type of school, standard of intake, class sizes and student characteristics have been shown to have an important impact on attainment (Warrington & Younger 2001, Sammons et al. 1993, Bondi 1991) and the investigation and measurement of school effectiveness is an important component of modern education research. At a time when schools and educational establishments as a whole are increasingly concerned with reaching and maintaining performance standards such research is vital in the field.

In any investigation into factors that influence educational attainment school effects should be considered where possible. The few school effects that can be examined here do reflect existing research (Smithers & Robinson 1995, Marks 1984) but for reasons explained in section 5.3 they are not investigated further here. This should be borne in mind when interpreting the results presented in this study (further discussion in chapter 8).

4.5 The next stage : Confirmatory Analysis

Preliminary analyses provide initial indications of the associations between social background factors and educational attainment, and also of trends in these associations. The next stage is confirmatory analysis which aims to model the effects of several social background factors on attainment simultaneously and to provide some interpretation of how these relationships change throughout the educational 'career'. To do so some form of statistical modelling is necessary. When using data from a longitudinal study such as BCS70 there are two main approaches to achieving this aim. The first is to use the data as a series of cross sectional studies and compare the results from one study to the next. This has the advantage that the same sample are used at each measurement occasion and so variation between samples is not a concern. The second approach is to model progress between measurement occasions. This is made possible as there are several consecutive reliable measures of educational attainment for each study member and hence progress from one measurement occasion to the next can be examined. Both approaches are used in the following chapters.

Statistical modelling of any multivariate data set is complex and methods suitable to the data being analysed must be employed. When dealing with survey data, particularly large scale survey data, it is unlikely that any one statistical method will be perfectly suited to data analysis. In practice, and often with some assumptions or manipulation of data, a variety of statistical models can usually be employed depending on the aim of the analysis. The following chapters detail analyses of BCS70 data using multilevel, log linear and ordinal logistic modelling as appropriate to the investigations being carried out.

Finally in exploratory investigations here, an overall education score is used at each follow up but such scores can often mask interesting trends within specific subjects. For example many studies examine attainment in mathematics and/ or English and have shown different social patterns in attainment and particularly in progress between the two. As more detailed test scores are available within the BCS70 for primary and secondary education, mathematics and English are investigated separately in chapter 5. Subsequently, overall scores are investigated again in later chapters.

Chapter 5 : Application of Multilevel modelling in BCS70

5.1 Introduction to multilevel models

Multi-level modelling is one of the most important developments in the statistical modelling of education data of recent times. The technique was first introduced in the late 1970s (Goldstein 1979) and the availability of computer software for multilevel modelling such as MLwiN (www.mlwin.com) has made it generally accessible to education researchers. Hence multilevel modelling has become widely used in quantitative educational research (Bock 1989, Goldstein 1987), and there are many instances of the technique being used to model effects of social background on educational achievements (Joshi et al. 1999, Sammons 1995, Paterson 1991, Plewis 1988) and in studies into school effectiveness (Schagen & Schagen 2005, Gray et al. 2001, Thomas et al. 1995, Sammons et al. 1993, Jesson & Gray 1991, Aitken & Longford 1986).

Multilevel modelling allows hierarchical structures within a social system to be taken into consideration in the modelling process. The education system is a typical example of a hierarchical structure where pupils are grouped within classes within schools within education authorities and so on. Multilevel techniques are particularly useful for examining causal mechanisms and estimating the effects of explanatory variables at all levels of the hierarchy on educational outcomes. For example attainment is influenced by factors associated with an individual's social background and will be different for each individual. The learning environment and factors associated with the school attended have also been shown to be influential. For example, average attainment of pupils within a school may be more similar than average attainment in other schools due to school based factors having an impact on overall and individual attainment. Multilevel modelling allows explanatory variables to be defined at every level if the information is available but is flexible in that variation at different levels can be considered whether explanatory factors are available or not. Other less obvious hierarchies can also be considered multilevel, for example longitudinal data where measurements are made at repeated time intervals can be considered a multilevel system. In this case repeated measurements at different occasions are grouped within individuals (Goldstein et al. 1994, Plewis 1993, Goldstein 1987) which can then in turn be grouped at higher levels, such as schools.

While the multilevel structure of the education system should be incorporated into the modelling of education data (Goldstein 1987), it is not always possible to do so. In this chapter the potential for multilevel modelling of BCS70 data is explored. Two different multilevel applications are illustrated. The first utilises the standard hierarchical aspect of the education system and reveals limitations of multilevel modelling in analysing BCS70 data as important levels within the education hierarchy cannot be identified. Nevertheless the analyses undertaken are useful in investigating variation at the various hierarchical levels that can be determined, and provide some evaluation of the effects of gender, ethnic group and social class on educational attainment and progress. The second multilevel application demonstrates the longitudinal aspect of the repeated measures multilevel model and provides some understanding about variability in attainment between the different measurement occasions. In the following analyses two aspects of education, mathematics and English are analysed separately as previous studies have shown differences in attainment and progress in these areas (Feinstein & Symons 1999, Brandsma and Knuver 1989, Goldstein 1979).

5.2 Attainment in Mathematics and Reading

Attainment in mathematics and English at age 16 is based on the grade achieved in mathematics and English language O level or CSE examinations using the point score system outlined in table 4.6. Examination of progress requires longitudinal data so that comparable measures of previous attainment are also available. In BCS70 test scores achieved in a mathematics test at age 10 are available but there is no exact match for English. Instead the score achieved in a reading test at age 10 is used to investigate progress in English. This is justified by the fact that there is a strong correlation ($r=0.64$, $p>0.05$) between reading test scores at age 16 and English language O level in a similar national birth cohort, the National Child Development Study. It is assumed that a similar relationship exists in BCS70 (Mc Niece et al. 2004). There are no comparable mathematics and reading scores at age 5.

Preliminary examinations of the associations between attainment in mathematics and English and the explanatory factors gender, social class and ethnic group are carried out in advance of multilevel modelling of the data, to provide an insight into possible patterns and trends. Examination of percentage differences between mean scores (adjusted for scoring ranges) show that girls appear to be better at English than boys towards the end of primary education i.e. age 10 (table 5.1). The trend continues and seems to increase (increase in percentage difference) between ages 10 and 16 with girls outperforming boys at O level. This would suggest that girls make more progress in

English than boys during secondary education. In mathematics the opposite appears to be true, boys achieve higher scores than girls at ages 10 and 16 and the gap widens during secondary education with boys outperforming girls in mathematics O level.

Table 5.1 : Percentages differences in mean scores = (difference in scores/ range)*100

	Maths		English	
	Age 10	Age 16	Age 10	Age 16
Gender				
Girls	-1.9	-6.6	2.3	3.7
(baseline = boys)				
Social class				
Professional	12.8	16.7	16.2	14.1
Skilled	3.9	4.3	5.2	3.6
(baseline=semi & unskilled)				
Ethnic group				
Non-U.K.	-8.4	-8.1	-10.9	-5.0
(baseline = U.K - white.)				

The figures also show that children from professional backgrounds achieved much higher scores than those from the less advantaged social classes, in both mathematics and English at both occasions. Similarly those from skilled backgrounds achieved higher scores than those from the semi and unskilled group although the gap between these groups is smaller than that between the professional and skilled groups. The figures suggest that the gap in mathematics attainment between the different social classes widened over the period with an increase in percentage mean difference. In English, the attainment gap appears to reduce slightly over the same period with decreases in percentage differences for both professional and skilled groups.

Figures in table 5.1 also indicate that ethnic minority students do not perform as well as the white group overall. There is little change in mean scores in mathematics between ages 10 and 16 suggesting that there is neither an improvement nor a deterioration in the mathematics attainment of ethnic minority children compared to the white group. In English the percentage difference in mean scores decreases between ages 10 and 16 which could indicate that the ethnic minorities made more progress in English during secondary education.

Correlations (table 5.2) indicate strong associations between achievements at age 10 and at age 16 and suggest that those who have reached a high standard by the end of primary education are likely to perform well again at age 16 in both mathematics and English. Correlations also indicate that a high score in English is associated with a high score in mathematics, and similarly a low score in English with a low score in mathematics, both at the end of primary education and at age 16.

Table 5.2 Correlations between test scores at successive measurement occasions

	Math10	Math16	Reading10	English16
Math10	1.000			
Math16	**0.594**	1.000		
Reading 10	**0.718**	0.492	1.000	
English16	0.501	**0.619**	**0.581**	1.000

All correlations significant at 0.05 level

5.3 Application of Multilevel modelling to BCS70 data

Initially it appears that four levels of the education hierarchy, pupils (level 1) within schools (level 2) within LEAs (level 3) within regions (level 4), and associated explanatory variables could be identified at ages 5,10 and 16. However this was not the case when this analysis was carried out as there was no substantial information about the schools attended in the BCS70 data set (section 4.3.7). There was no available information that would allow identification of different schools (for modelling purposes) and hence no way of defining the school level, associated factors and variation. Subsequently the scope for using multilevel models for thorough analyses of the data was limited when this research was carried out. The aim of showing multilevel applications here is to illustrate how they might be used to model the type of longitudinal education data found in BCS70. Any investigation into the potential of a dataset for educational research should consider the use of multilevel modelling as it is particularly suited to analysing education data.

Even with the limitations of investigating school based factors, multilevel modelling still has valuable applications to BCS70 data. Two basic multilevel models are described and illustrate ways in which the methods can be applied to longitudinal hierarchical data. The first examines the three level hierarchy, individuals within LEAs within regions, and utilises the longitudinal aspect of BCS70 data by examining progress in attainment. The second is a repeated measures model which illustrates the use of multilevel models from a different longitudinal perspective. The results of both applications are presented and discussed to illustrate how the techniques might be used in determining the effects of social background on educational attainment and progress.

5.4 Three level progress model for BCS70 data

A three level hierarchical structure with students grouped within LEAs grouped within regions as shown in figure 5.1 can be identified in BCS70. Multilevel modelling is used to investigate variation in educational outcomes at each of the three levels. Attainment in mathematics and English are analysed separately and a three level 'between occasion' (Goldstein 1987, 1979) model is used to investigate progress in both subjects between the end of primary education (age 10) and the end of compulsory secondary education (age 16). The regression based part of the model (equation 5.1) is designed to examine progress by regressing score achieved at O level against a corresponding earlier test score and to study the relationships between progress and social background factors.

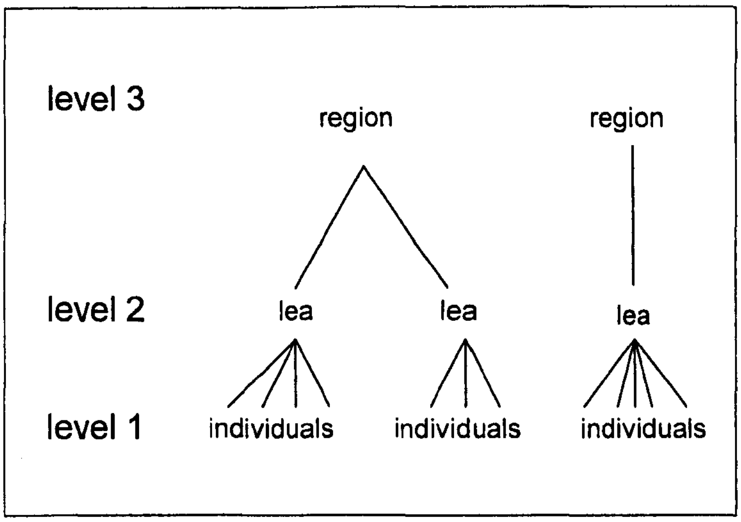


Figure 5.1

The model (equation 5.1) is a multilevel regression based variance components model where an assumed continuous response (see section 2.2) is regressed on one or more fixed explanatory variables which can be defined at some or all levels, or across levels for more complex situations (Goldstein 1986a). Here, attainment at age 16, measured by scores achieved in O levels and equivalent examinations, is regressed on five explanatory variables; a continuous variable representing corresponding score at age 10 and dummy variables representing ethnic group, gender, professional social class (RG's

I & II) and skilled social class (RG's IIINM) background. All explanatory variables are modelled at the individual level, level 1. There are no explanatory variables at the higher levels. The multilevel model applied to the data here is

$$y_{ijk} = \beta_0 + \sum_{r=1}^{5} \beta_r x_{rijk} + (\gamma_k + \mu_{jk} + e_{ijk})$$

(model 5.1)

where y_{ijk} : point score achieved at age 16 in O level/ CSE (mathematics or English)

β_0 intercept

β_r parameter estimate associated with explanatory variable r, r= 1...5

x_1 : score (mathematics or English) achieved at age 10

x_2 : ethnic group

x_2 : gender

x_4 : professional social class

x_5 : skilled social class

i denotes level 1 - individuals

j denotes level 2 - LEAs

k denotes level 3 - regions

γ_k : level 3 variation (i.e a random effect which varies only at level 3, regions)

μ_{jk}: level 2 variation (i.e. a random effect which varies at level 2, LEA and is the same for every student in LEA j)

e_{ijk}: level 1 variation (i.e. a random term which varies at level 1, individuals, different for every individual).

Random terms are assumed to be normally distributed where

$E(e_{ijk})=0$, $var(e_{ijk})= \sigma^2$, $cov(e_{ijk},e_{ijl})=0$

$E(\mu_{jk})=0$, $var(\mu_{jk})= \sigma_\mu^2$,$cov(\mu_{jk},\mu_{jl})=0$

$E(\gamma_k)=0$, $var(\gamma_k) = \sigma_\gamma^2$,$cov(\gamma_k, \gamma_l)=0$

The model can be considered as an extension of the basic linear regression model but instead of having a single term for variance (error) the total variation is partitioned into more than one component, hence variance components. It has a fixed or 'regression based' part, $\beta_0 + \sum_{r=1}^{5} \beta_r x_{rijk}$, and a random part $(\gamma_k + \mu_{jk} + e_{ijk})$ consisting of random components for all three levels.

Modelling is carried out using MLwiN, a package developed specifically for multilevel modelling and capable of running large scale multilevel analyses. As with most longitudinal studies missing data is common in BCS70 and as MLWin ignores records with missing data in analyse. The results are based on a substantially reduced sample size of approximately 4000 pupils (for whom full data is available) within 113 LEAs within 12 regions. All test scores are standardised before analysis to eliminate differences due to different scoring ranges.

The model is fitted and the parameters estimated using an iterative generalised least squares (IGLS) procedure as detailed in Goldstein (1986b, 1987). The analysis provides parameter estimates representing the effect of each of the explanatory variables and estimates of the variation between test scores at the individual level, variation between groups of pupils within LEAs and variation between the groups of LEAs within regions. Interpretation of the parameter estimates is based on confidence intervals as these give a better indication of the true values of a parameter than point estimates and can help determine whether or not explanatory variables have any practical effect on attainment. The adequacy of the model is assessed by examining goodness of fit statistics and the results of the three level analysis of BCS70 data are shown in table 5.3.

5.4.1 Results of three level progress model

MLWin estimates the parameters for explanatory variables against a reference or baseline group, usually the lowest category of each explanatory variable. The baseline for the analyses here is white boys from semi & unskilled backgrounds (RG's IIIM, IV and V). The three level progress model with all five explanatory variables is fitted initially (results in table 5.3) and examination of parameter estimates shows that the ethnic group factor is not statistically significant[1] in mathematics attainment. Model fit was not significantly affected when the model was rerun without ethnic group, hence it can be concluded that ethnicity is not a significant factor in mathematics progress between the end of primary (age 10) and the end of compulsory education (age 16). However for English Language ethnic group is a significant factor in progress, and so ethnic group is retained as an explanatory factor in modelling progress in English Language.

[1] a significance level of α=0.05 is used throughout

Table 5.3 : Results from three level progress model with all 5 explanatory variables

	Parameter estimate	Standard Error
Mathematics		
Fixed		
Constant	-0.461	0.042
Previous Math	0.605 *	0.015
Female	0.111 *	0.026
Non-white	0.070	0.083
S.class 1 (prof)	0.352 *	0.044
S.class 2 (skilled)	0.093 *	0.042
Random		
Region var(γ_k)	0.017	0.009
LEA var(μ_{jk})	0.006	0.004
Individual var(e_{ijk})	0.607	0.014
N	*3640*	
English Language		
Fixed		
Constant	-0.309	0.052
Previous reading	0.629 *	0.015
Female	-0.202 *	0.026
Non-white	0.306 *	0.083
S.class 1 (prof)	0.318 *	0.043
S.class 2 (skilled)	0.067	0.041
Random		
Region var(γ_k)	0.010	0.006
LEA var(μ_{jk})	0.010	0.004
Individual var(e_{ijk})	0.622	0.014
N	*3840*	

* = significant, α=0.05

'Constant' represents the baseline category

As attainment at age 16 is modelled conditionally on attainment at age 10 the outcome investigated is progress made between the two occasions (Plewis 1997, Goldstein 1987), i.e. between the end of primary education and the end of compulsory education, rather than just attainment at age 16. The effects of explanatory factors on progress are indicated by the relevant parameter estimates. In general, positive coefficients indicate more progress and negative coefficients indicate less progress. The 'Constant' parameter in table 5.3 represents the baseline group.

5.4.2 Interpretation of results – Effect sizes

The parameter estimates obtained from multilevel modelling can indicate the nature of the association between progress and the explanatory variables and indicate whether or not the effects are statistically significant but they do not provide any information about the impact or size of the effect. Effect sizes (section 2.5) can provide more meaningful estimates of the effect of an explanatory variable and allow the effects of different explanatory variables to be directly compared with each other. Effect sizes are only calculated for statistically significant variables (Strand 2002). Here effect sizes are calculated using the methods outlined by Elliot & Sammons (2004) and Strand (2002). They suggest that suitable estimates of effects sizes can be calculated as

For categorical variables

$$ES = \frac{\text{categorical predictor coefficient}}{\sqrt{\text{child level variance}}}$$

These effect sizes can be interpreted as 'the estimated means for the groups defined by the dummy codings 1 and 0 expressed as a fraction of the pupil level standard deviation, after appropriate controls have been made'. (Tymns et al. 1997)

For continuous variables

$$ES = \frac{\text{continuous predictor coefficient} * 2(\text{SD continuous predictor variable})}{\sqrt{\text{child level variance}}}$$

In this case the effect size represents the 'change on the outcome due to a change of +/- one standard deviation on the continuous predictor' (Elliot & Sammons 2004)

Table 5.4 : Effect sizes for three level model

	Variable type	Calculation	Effect size
Mathematics			
Previous Math score	Continuous	$\frac{0.605 * 2(1)}{\sqrt{0.607}}$	1.55
Female	Categorical	$0.111/\sqrt{0.607}$	0.14
Non-white (ns)	Categorical		
S.class 1 (prof)	Categorical	$0.352/\sqrt{0.607}$	0.45
S.class 2 (skilled)	Categorical	$0.093/\sqrt{0.607}$	0.12
English Language			
Previous reading score	Continuous	$\frac{0.629 * 2(1)}{\sqrt{0.014}}$	1.60
Female	Categorical	$-0.202/\sqrt{0.014}$	-0.26
Non-white	Categorical	$0.306/\sqrt{0.014}$	0.39
S.class 1 (prof)	Categorical	$0.318/\sqrt{0.014}$	0.40
S.class 2 (skilled) (ns)	Categorical		

ns – not statistically significant, $\alpha=0.05$

The continuous predictors, i.e. test scores in mathematics and reading at age 10, were standardised before analysis, therefore the standard deviation for both variables is 1.

Social class

The social class parameter estimates indicate that class has a significant effect on general educational attainment and progress between ages 10 and 16. This is most noticeable in the attainment of those from the professional and managerial social classes who perform better and make more progress during secondary education than those from the other, less advantaged classes in both English language and mathematics. The effect of coming from the professional social class is greater for mathematics (0.45) than for English (0.39) but for both subjects professional social class has the greatest impact on attainment. Those from skilled backgrounds made significantly more progress (0.12) than those from the semi & unskilled group in mathematics, but there was no significant difference in progress in English language between these two social groups.

Gender

The results also show that progress in mathematics and English differs between the sexes. Historically boys have performed better in mathematics than girls, but the gap between the sexes is reported to have diminished since the mid-eighties with girls now achieving comparable and often better results in mathematics than boys (Woodward 2002). Preliminary examinations of percentage differences in mean scores in mathematics indicated that boys achieved higher scores than girls at ages 10 and 16 and that the attainment gap increased during this period, i.e. percentage mean difference increased (table 5.1). However the multilevel model results show that girls actually made more progress in mathematics than boys between ages 10 and 16, reflecting research findings and contradicting what was inferred from preliminary analyses.

Traditionally boys have been less successful than girls in English language. Preliminary investigations reflect this indicating that boys achieve lower scores on average than girls at ages 10 and 16 and that the gap between the sexes increased during secondary education. The results of the multilevel analysis carried out here indicate that boys actually made more progress than girls in English Language during secondary education, again contradicting indications from preliminary investigations. Effect sizes indicate that while girls make more progress than boys in mathematics (0.14), boys actually make more progress than girls in English (girls progress in English = -0.26, hence boys progress in English = 0.26). However, overall, gender effects are smaller than social class effects.

Ethnic group

Differences in average overall scores between the white and ethnic minority groups (table 4.11) indicate that overall attainment among the ethnic minorities is much lower than among whites which reflects research findings from around the time that the study was conducted (Drew & Gray 1990, Plewis 1988). Preliminary investigations also indicate that the ethnic minority group have lower average attainment in both mathematics and English throughout the education system. Further, while the gap between ethnic groups remains more or less unchanged in mathematics during secondary education, it seems to decrease in English during the same period. The results of multilevel modelling reflect these findings indicating that there is no significant ethnic group effect on progress in mathematics. On the other hand ethnicity does appear to have a significant effect on attainment in English with the ethnic minority group making significantly more progress in English during secondary education than the white group. In fact the ethnic group effect is almost as strong as the professional social class effect (0.39 compared to 0.40 respectively) in English. It is worth noting that these findings should be interpreted with caution as they are based on a small sample which in turn is only a very small proportion of the BCS70 cohort (3%), (see section 5.6).

Region and LEA

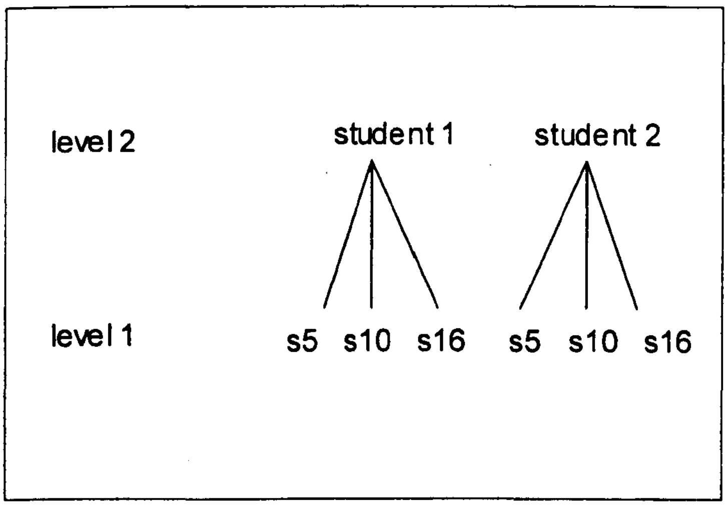
Preliminary investigations indicated slight differences in average attainment between regions although this may reflect the different social class compositions of regions rather than any real difference in abilities. Including social class as an explanatory variable in the model has the effect of controlling for the different social class compositions of the various regions. In the analyses for both mathematics and English, less than 4% of the total variation is due to the differences between regions and LEAs and virtually all the variation occurs at the individual level for both mathematics and English. Hence it can be concluded that, after allowing for the social composition of the regions by including social class in the model, there is no significant difference in average attainment in O level mathematics or English Language between the different U.K regions. Similarly there is no significant difference in attainment between LEAs. Almost all of the variation in O level attainment occurs at levels of the education hierarchy lower than LEAs and regions, that is, at the school, class and individual levels.

Here, the remaining variation cannot be split between the school, classroom and individual levels as schools and classes cannot be identified, so all of this variation appears at the individual level in the results. In interpreting the effects of explanatory variables on attainment it must be borne in mind that attainment will also be subject to influences from school and classroom level effects which are not accounted for here.

5.5 Repeated measures model

Longitudinal data exhibit another form of hierarchical structure where the same or similar measures are recorded for each individual at several points in time, hence giving a series of repeated measures. The repeated measures multilevel model can be used to examine variation between such repeated measures. In BCS70 measures of educational performance at each of the first three follow up studies provide a profile of attainment at important points in the education system. The test scores at each occasion can be considered as repeated measures and add another level to the education hierarchy (Goldstein 1987) with test scores grouped within individuals within LEAs within regions.

The results of the three level model (section 5.4.1) have shown variation at LEA and regional levels to be negligible and so just two levels are considered here. In this case the level one observations are the scores achieved on the different successive measurement occasions grouped within individual students who are now the level 2 observations as shown in figure 5.2.



(n.b. s5, s10 and s16 represent test scores at ages 5, 10 and 16)

Figure 5.2

The model used (equation 5.2) is a two level regression based variance components model and could easily be extended to include higher levels in the hierarchy. One of the main advantages of this model is that it can cope with data missing at random and hence it is not necessary to have equal numbers of level 1 measures for each individual (McDonald 1993), a particularly useful attribute when dealing with longitudinal studies where missing data is common. Hence maximum sample sizes can be maintained. The two level repeated measures model applied to the BCS70 data is

$$y_{ij} = \beta_0 + \sum_{r=1}^{4} \beta_r x_{rj} + (\mu_j + e_{ij})$$

(equation 5.2)

where y_{ij} score achieved in test (at any age) by individual j

β_0 intercept

β_r parameter estimate associated with explanatory variable r, r= 1...4

x_1 : ethnic group

x_2 : gender

x_3 : professional social class

x_4 : skilled social class

i denotes level 1 (test scores) i =1..3 (ages 5, 10 and 16)

j denotes level 2 (individuals) j =1...n (n individuals)

μ_j: level 2 variation (i.e. a random effect which varies for each individual)

e_{ij} : level 1 variation (i.e. a random term associated with the i^{th} test score for each individual, different for every test score).

Random terms are assumed to be normally distributed where

$E(e_{ij})=0$, $var(e_{ij})= \sigma^2$, $cov(e_{ij},e_{ik})=0$

$E(\mu_j)=0$, $var(\mu_j)= \sigma_\mu^2$,$cov(\mu_j,\mu_k)=0$

The response y_{ij} is the test score achieved on occasion i (level 1) by individual j (level 2) and x_{rj} indicate explanatory social characteristics of the individual j. As before scores are regressed on dummy explanatory variables, ethnic group, gender and two social class categories, professional and skilled. Explanatory variables are defined at level 2, the individual level. Here the random part of the model has two components, variation between the individuals (μ_j) and variation between measurement occasions (e_{ij}). Results from the repeated measures analysis are shown in table 5.5.

5.5.1 Results of Repeated measures model

The repeated measures model allows variation in scores at the individual level to be examined, which was included in the individual level variation in the three level model. The baseline is the same as for the three level model, i.e. white boys from semi & unskilled backgrounds and the results of the analysis are given in table 5.5. Effect sizes are given in table 5.6.

Table 5.5 : Results from two level repeated measures model

	Parameter estimate	**Standard error**
Mathematics		
Fixed		
Constant	-0.412	0.023
Sex	0.162 *	0.017
Ethnic	-0.331 *	0.047
S.class 1 (prof)	0.696 *	0.026
S.class 2 (skilled)	0.199 *	0.024
Random		
Level 2 var(μ_{jk})	0.452	0.013
Level 1 var(e_{ijk})	0.450	0.010
N(no. of scores)	*15612*	
English Language		
Fixed		
Constant	-0.814	0.043
Sex	-0.027	0.014
Ethnic	-0.527 *	0.041
S.class 1 (prof)	0.685 *	0.022
S.class 2 (skilled)	0.231 *	0.020
Random		
Level 2 var(μ_{jk})	0.316	0.009
Level 1 var(e_{ijk})	0.598	0.008
N (no. of scores)	*15554*	

* = significant α=0.05

' Constant' represents the baseline category

Table 5.6 : Effect sizes for repeated measures model

	Variable type	Calculation	Effect size
Mathematics			
Sex	Categorical	$0.162/\sqrt{0.452}$	0.24
Ethnic	Categorical	$-0.331/\sqrt{0.452}$	-0.49
S.class 1 (prof)	Categorical	$0.696/\sqrt{0.452}$	1.03
S.class 2 (skilled)	Categorical	$0.199/\sqrt{0.452}$	0.30
English Language			
Sex (ns)	Categorical		
Ethnic	Categorical	$-0.527/\sqrt{0.316}$	-0.94
S.class 1 (prof)	Categorical	$0.685/\sqrt{0.316}$	1.22
S.class 2 (skilled)	Categorical	$0.231/\sqrt{0.316}$	0.41

ns – not statistically significant $\alpha=0.05$

This repeated measures multilevel application does not provide any new insights into the effects of social background factors on attainment but it does confirm the inferences about the size of effects from the three level model. Social class is still a significant factor, with those from the professional and managerial groups attaining higher scores in tests than those from the other social class groups and the effect of being from a family in the professional class being much greater than that of the skilled class (1.03 and 0.30 respectively in mathematics and 1.22 and 0.41 in English respectively). Boys are shown to perform significantly better than girls in mathematics overall (as for preliminary findings table 5.1) but there is no overall difference between the sexes in English. This may be due to the fact that differences have balanced out over time as preliminary investigations showed that girls significantly outperformed boys in the early years but that boys made more progress in reading between ages 7 and 16. This would suggest that overall the effects of gender on attainment in English are negligible by the end of compulsory education. The effect of ethnic group is again a significant explanatory factor in both mathematics and reading, with the ethnic minority group achieving lower scores on average than the white group and the size of the effect being greater in English than in mathematics.

The components of variance (table 5.5) relating to the two levels in the model indicate that while there is significant variation between test scores at the individual level there is also much variation between individual's scores on the different measurement occasions, 50% (0.452/0.452+0.450) and 35 % (0.316/(0.316+0.598) of the total variation in mathematics and English respectively. Preliminary investigations of correlations (table 5.1) between test scores indicated that scores achieved towards the end of primary education are strongly correlated with attainment at age 16 and the three level model confirms this. This would suggest that although there is a lot of change between an individual's test scores on different occasions (two level model) most of this change occurs during the primary years rather than during secondary education. Further this would suggest that early educational achievements are probably not good indicators of attainment further into the education career in mathematics and English but there is no way of determining trends in attainment and development within primary education in the BCS70 data.

5.6 Discussion of multilevel modelling

The use of multilevel modelling to investigate BCS70 data presented here is more to illustrate suitability of the model rather than to draw substantial conclusions about the effects of social background on educational attainment. Even within the limitations of the analysis some useful conclusions can be drawn and some important points are raised. Similarly the effect sizes presented here are mainly for illustration and are not reliable estimates of the true effects of class, gender and ethnicity as they include variation due to other known significant factors, for example parents' education and school effectiveness factors.

The results show some of the recognised changes in educational trends that were emerging in the mid-eighties. For example girls had begun to catch up with boys in attainment in mathematics. At the same time however, the results show that boys were actually making more progress in English language during secondary education than girls, a trend that was not well reported at the time. This finding also contradicts indications from the preliminary investigations which suggested that the gender gap in English attainment between ages 10 and 16 widened. Hence reinforcing the importance of appropriate statistical modelling in understanding the true effects of background factors on attainment.

Multilevel analyses also provide an insight into social class and ethnic trends in educational progress during secondary education. The results show an increasing attainment gap between children from advantaged backgrounds and those from less advantaged backgrounds. While the analyses can reveal such social patterns in progress it is not so easy to interpret the cause of the effect. On one hand the lower social classes could be achieving a similar standard in English language as the middle social group, suggesting that they are making more progress. Alternatively the results could indicate an increasing attainment gap between the most advantaged class (RG's I &II) and other social groups. A comparison of these findings against an earlier study using NCDS data (McNiece et al. 2004) suggests that the latter is more likely. Such findings are worrying as they suggest that secondary level education is somehow failing all but the most advantaged classes when it comes to English language skills.

The results also show that ethnic minorities were perhaps doing better than previous research suggests, by maintaining the same level of progress in mathematics and actually making more progress in English during secondary education than the white group. There could be many reasons for this apparent, marked improvement in English attainment including education policy (Swann 1985) and home life factors. A possible explanation could even be that in the 1970s English was not the first language used in the home for some ethnic minority children. In such cases the children would almost certainly have been at a disadvantage in English language during the early education years compared to the white group. As they progressed through the education system their English skills would have developed and the disadvantage diminished with the result that during secondary education ethnic minority children actually make more progress in this subject than their white counterparts. Even though these findings are based on a very small sample they are indicative of the more recent research findings which showed that ethnic minorities made more progress than white students between key stages 3 and 4 of the national curriculum (Haque & Bell 2001).

The process of multilevel modelling also raised some important issues in using BCS70 data for education research in general. As previous exercises have shown (chapter 3) the complexity and nature of data collection in longitudinal studies can lead to frequent missing data which can limit the scope for statistical analysis. Attrition of the sample over time is inevitable (Menard 1991) but in general large surveys such as BCS70 should provide adequate samples for statistical analysis.

However item non-response does pose a greater problem in statistical analysis as most statistical packages ignore records with missing data. For example, response to the details of examinations was good with detailed education information available for 7336 study members. However missing data on the variables in the three level analysis quickly leads to a reduction in sample size of almost 50%. The repeated measures model was not so badly affected by missing data as it does not require an observation, in this case a test score, at every measurement occasion. This is a useful attribute for analysing longitudinal data, particularly that collected over a long period of time where there is increased opportunity for non-response. Here students who were not included in the three level model due to missing education scores would have been included in the repeated measures model and the effects of social factors on attainment could still be examined, hence maximising sample size. However progress could not be investigated with this model.

The potential for using multilevel modelling to investigate education data in BCS70 is restricted due to the fact that important levels in the education hierarchy, i.e. class and school, could not be identified and hence considered in the modelling process. In the analyses here variation in progress due to different schools, classes and associated explanatory factors is incorporated into the individual level component of variance and cannot be separated out. If schools could have been identified, it is unlikely that there would be many children in any one class or even in one school with a birthday in the same week. Investigation of the effects of individual schools would not have been practical as there are more than one thousand different schools in the sample and interpretation of effects due to individual schools would be challenging. The value of multilevel modelling in this case would have been in the opportunity to investigate explanatory factors at the school level, such as type of school, size of class, whether the school provided mixed or single-sex education and intake characteristics of the students. The facility for investigating school factors in this way makes multilevel modelling particularly suitable for school effectiveness studies and the technique is widely used in this area (Gray et al. 2001, Sammons et al. 1993, Patterson 1991, Brandsma and Knuver 1989). In general multilevel modelling techniques play an important role in helping researchers to understand how different factors affect attainment across all levels of the education hierarchy. The techniques and associated software are continually being developed and extended to deal with a wider range of investigations and for applications to more complex data structures (Fielding et al. 2003, Goldstein et al. 2002, Yang et al. 2000). Detailed explanations of more complex multilevel models and the statistical theory underlying multilevel models can be found in the relevant literature and are particularly well defined by Goldstein (1987), Duncan et al. (1994) and Plewis (1997).

In summary, the analyses presented here show that longitudinal studies are valuable in monitoring social trends in education and in detecting changes which might be missed by a series of cross sectional studies. Longitudinal data are particularly valuable in investigating educational progress. The scope for such investigation using BCS70 was limited at the time when these analyses were carried out but as the information has now been made available (August 2005) there is much greater potential for investigating BCS70 data to the full extent of the education hierarchy, using multilevel modelling.

Chapter 6 : Log linear modelling of BCS70 data.

6.1 Introduction

In education research standard statistical modelling techniques are commonly used for analysing data but often using these techniques involves making assumptions about the data, particularly the outcome variable, which are not always strictly valid. For example, multiple linear regression (MLR) is often used to model educational outcomes even when there is no real continuous distribution underlying the outcome variable. Many educational outcomes are categorical and in such cases the MLR model is not an appropriate statistical method for analysis, even with assumptions. Similarly, standard logistic regression is commonly used to model categorical education outcomes. While this method is appropriate it limits the scope of analysis to a dichotomous outcome variable and often educational outcomes that have more than two categories are collapsed to meet the requirements of logistic regression. This can lead to a loss of valuable information. When educational outcomes and social background variables are measured on categorical scales statistical modelling techniques for categorical data are more appropriate for data analysis. Other logit based models that can be used for the analysis of outcomes with more than two categories may provide better alternatives but they are under utilised in education research.

Log linear modelling is one such technique which may be suitable for investigating multiple category education outcomes. In this chapter the scope of log linear modelling for analysing BCS70 data is investigated. An advanced version of the standard log linear model that can account for the ordinal nature of factors is applied to the data to investigate the nature and magnitude of associations between social background factors and educational attainment. The same model i.e. the same set of variables, is used to analyse the data at ages 5, 10 and 16 so that the effects of such social factors and how they change over time can be examined.

6.2 Log linear models

Log linear models belong to the family of generalised linear models (GLMs). They are used when data can be considered as counts in a multidimensional contingency table, where each cell represents a distinct combination of a set of categorical variables (Dobson 1990, McCullagh & Nelder 1989). The technique is based on the principle that the logarithm of cell counts can be modelled as a linear function of all the factors in the model (Agresti 2002). The modelling process produces estimates that can then be used to evaluate the probability of falling into a particular combination of factor categories using the linear predictor function. As the cell frequencies are counts and cannot take negative values, the random components of the model (error terms) are assumed to follow a Poisson distribution.

In theory the log linear model does not actually distinguish between outcome and explanatory variables but rather investigates the associations between all variables in the model. The cell frequencies within each combination of factors are the objects of analysis and the model fits expected frequencies to the individual cells. Therefore the outcome or response in a log linear model is really the cell frequency. However, often in practice, one of the variables is of particular interest and the aim of modelling is to investigate the effect of the other variables in the model on the variable of interest. For example, in the following log linear analyses, educational attainment is the outcome and interest lies in the associations between attainment and the other (explanatory) factors in the model. With careful interpretation of the parameter estimates log linear models can be used to examine the effects of social background factors on educational attainment.

In general the log linear model can be represented as:

$$\ln(f_{ij}) = \mu + \sum_r \lambda_r$$

(equation 6.1)

where $ln(f_{ij})$ = log of the frequency (f) in cell ij

μ = constant

λ_r = parameter estimate associated with factor r

i= 1,..,m where there are m rows

j= 1,..,n where there are n columns

Hence cell counts can be estimated by reversing the transformation;

$$f_{ij} = \exp(\mu + \sum_r \lambda_r)$$

(equation 6.2)

The simplest form of the log linear model is the two factor model which can be represented by a two way contingency table, where factors A and B have i and j categories. The saturated model consists of main effects due to each factor, and an interaction between the two factors A and B (equation 6.3).

$$\ln(f_{ij}) = \mu + \lambda_i^A + \lambda_j^B + \lambda_{ij}^{AB}$$

(equation 6.3)

where f_{ij} = expected cell frequency in row i and column j

μ = constant

$\lambda^A{}_i$ = main effect due to category i (row i) of factor A

$\lambda^B{}_j$ = main effect due to category j (column j) of factor B

$\lambda^{AB}{}_{ij}$ = interaction between category i of factor A and category j of factor B

Log linear modelling is most useful for investigating relationships in contingency tables of three or more dimensions. The basic two factor model extends easily to higher dimension tables for any number of factors with the main effects and interaction terms building accordingly. However, as the number of factors in an analysis increases, the corresponding tables quickly increase in size and become difficult to report and interpret. Higher order interactions are particularly difficult to interpret. In general the aim of log linear modelling for higher dimension contingency tables is to find the most parsimonious model that adequately fits the data and allows the associations within the table to be interpreted.

6.3 Log linear models for ordinal categorical data

Standard log linear models (equation 6.1) treat all variables as nominal but adaptations of the model can be applied where there is some order to the variables. There are two main types of ordinal log linear model, suitable to the educational and social data being considered; the linear by linear (or ordinal by ordinal) association model and the row or column effects (ordinal by nominal association) model. Both are extensions of the standard log linear model and detailed descriptions can be found in Agresti (2002), Ishii-Kuntz (1994) and Gilbert (1993).

6.3.1 The linear by linear association model

The linear by linear association model can be used to model two ordinal variables. Consider a two factor log linear model where both factors are ordinal, for example educational attainment and social class. Hence rows i and columns j represent increasing attainment and increasing social class respectively (figure 6.1).

	Social class		
Attainment	1 (low)	2 (middle)	3 (high)
1 (below average)			
2 (average)			
3 (above average)			

Figure 6.1

The standard saturated model (equation 6.3) replicates the data exactly and estimates interactions for all combinations of attainment and social class, in this case nine separate interaction parameter estimates. While these interactions describe exactly the associations between every combination of attainment and class, they are very detailed and often a summary of the overall association is preferable in terms of presenting and interpreting results. Removing the interaction term from the model gives the main effects model (equation 6.3 without λ_{ij}^{AB} term) which does not estimate any association between the two variables and rarely provides a good fit for data. Ideally a model that lies somewhere between the main effects and the saturated model is required. The linear by linear association model (equation 6.4) provides such a model and estimates a single interaction term which describes the association between the two variables (Agresti 2002, Green 1988).

$$\ln(f_{ij}) = \mu + \lambda_i^A + \lambda_j^B + \beta(a_i - \bar{a})(b_j - \bar{b})$$

(equation 6.4)

Where f_{ij} : cell frequency

μ : constant

λ_i^A : main effect for factor A (e.g.attainment)

λ_j^B : main effect for factor B (e.g. social class)

i = level of factor A

j = level of factor B

β = coefficient of association (e.g. between attainment and social class)

a_i = known values of factor A

$\bar{a}$ = mean value of factor A

b_j = known values of factor B

$\bar{b}$ = mean value of factor B

In effect the usual interaction term between two variables is replaced by a regression term with coefficient β estimating the linear relationship between the two variables. One estimate of the coefficient applies across all categories of the ordinal variables providing a general summary of the association. In general if β is positive (and significant) then there are more observations in cells where both variables are high and where both variables are low than would be expected under independence. A negative significant value of β indicates a negative association where there are more observations than expected in cells where one variable is high and the other is low (Agresti 2002). For example, in the case of educational attainment and social class, a positive value of β indicates that individuals from the higher (most advantaged) social classes are more likely to fall into the higher attainment categories and conversely the least advantaged classes are more likely to fall into the lowest attainment bands.

Finally the single interaction term gives a 'uniform association' which assumes that there is unit difference between each level of the ordinal variables i.e. all factor categories are equally spaced. In the example this means that there is the same difference between the lowest and middle social class groups as between the middle and highest social class groups.

6.3.2 The Row or Column effects (ordinal by nominal) model

The row or column effects model takes into account the ordinal nature of one of a pair of variables, for example it could be applied to model the relationship between educational attainment (ordinal) and gender (nominal). Hence rows i represent increasing attainment and columns j represent the different sexes (figure 6.2).

	Gender	
Attainment	1 (male)	2 (female)
1 (below average)		
2 (average)		
3 (above average)		

Figure 6.2

The model is similar to the linear by linear association model in that the general interaction term is replaced by an ordinal term. In this instance the ordinal term estimates a separate slope for each category of the ordinal variable. The two factor column effects model is

$$\ln(f_{ij}) = \mu + \lambda_i^A + \lambda_j^B + \alpha_j(a_i - \bar{a}) \qquad \text{(equation 6.5)}$$

where f_{ij}: cell frequency

μ: constant

λ_i^A : main effect for factor A (e.g.attainment)

λ_j^B : main effect for factor B (e.g. social class)

i = level of factor A

j = level of factor B

α_j = coefficient of association (e.g. between attainment and gender)

a_i = known values of factor A

$\bar{a}$ = mean value of factor A

The α_j terms are the column (or row) effects and estimates of α_j give the effect of each category of the nominal factor on the ordinal one. If $\alpha_j > 0$ then there is a higher probability of higher categories of factor A (attainment) in category j of factor B than would be expected under independence (i.e. there is a tendency towards the higher end of the scale) (Ishii-Kuntz 1994). Alternatively if $\alpha_j < 0$ then observations in category j of factor B are more likely to fall into the lower categories of factor A. For example, if the reference group is boys, then $\alpha_j > 0$ indicates that girls are more likely to fall into the higher attainment levels, if $\alpha_j < 0$ then girls are more likely to be in lower attainment groups than boys. For all column (or row) effects models $\Sigma \alpha_j = 0$.

The main advantage of ordinal log linear models is that the overall interaction parameters, β and α are easier to interpret than full interaction terms. This is particularly beneficial when variables have more than two categories and when examining patterns in high dimension models. Both the linear by linear and column (row) effects models can easily be extended to higher dimension models as additional factors are added to the analysis.

6.4 Analysis of BCS70 data using multidimensional ordinal log linear models

At the outset of the analysis eight factors were considered (educational attainment, social class, parents' education, sex, ethnic group, care, low income and family size - see appendix 4 for definitions) for inclusion in the log linear model. However, factors ethnic group, low income, care and family size all have categories with small numbers and introduced many zero cells into the associated 864 cell contingency table. A condition for log linear modelling to be valid is that no more than 5% of cells can have zero counts but the eight factor model far exceeded this.

In order to retain as much information as possible in the analyses factors low income, care and family size were combined into a single dichotomous factor indicating whether or not an individual had experienced any of these disadvantages, resulting in a single variable representing social disadvantage (see appendix 6). As the numbers of ethnic minorities in BCS70 is so small it is not feasible to include ethnic group as a factor in log linear analyses. Subsequently a five factor (educational attainment, social class, parents' education, sex, and social disadvantage) log linear model is applied to BCS70 data at each analysis time point, i.e. at ages 5, 10 and 16.

Attainment at age 16 is based on a categorical scale that is commonly used in education research and is grouped into three categories, i.e. no O levels, less than 5 O level passes and 5 or more O level passes (n.b. O level passes are defined as GCE 'O' levels grades A-C, CSE grade 1, Scottish Ordinary grades A-C and Scottish standard grades 1-3). This information is derived from raw BCS70 data collected on the family follow up form of the 1986 study. In order that models and analysis results can be compared over time overall test scores at ages 5 and 10 are collapsed to three attainment bands in similar proportions to the observations in attainment categories at age 16 (table 6.1). These bands are defined as below average, average and above average. Slight variations in the proportions in each attainment band at different ages are due to the fact that scores are classified to attainment bands based on the nearest cumulative frequency (see appendix 6).

Table 6.1 Percentage of cohort in each attainment band

	Age 5		Age 10		Age 16	
		%		%		%
Attainment Band	Below average	33.5	Below average	33.6	No O levels	33.6
	Average	35.2	Average	35.1	1-4 O levels	35.1
	Above average	31.3	Above average	31.3	5 + O levels	31.3

The normal procedure for fitting log linear models is to fit the saturated model initially and then remove terms from the model using a backward elimination approach. A further aim is to find the most parsimonious model for the data, ideally one with few high order interaction terms. Initially the saturated model is fitted and then high order interaction terms are removed in order, (i.e. five way interaction, then all 4 way interactions, then all 3 way interactions (appendix 6)). 'Goodness of fit' statistics measure how adequately a model describes the structure of a contingency table and are assessed by examining the deviance (change in the likelihood function) between two successive models (appendix 6). Log linear modelling can be affected by sample size with large sample sizes requiring more complicated models to get a good fit. Here a standard log linear model (no ordinality) including all 2 way interactions (equation 6.6) was found to give a good fitting model (table 6.3).

$$\ln(f_{ijklm}) = \mu + \lambda_i^{Att} + \lambda_j^{SC} + \lambda_k^{PE} + \lambda_l^{G} + \lambda_m^{SD} + \lambda_{ij}^{Att*SC} + \lambda_{ik}^{Att*PE} + \lambda_{il}^{Att*G} + \lambda_{im}^{Att*SD} + \lambda_{jk}^{SC*PE} + \lambda_{jl}^{SC*G} + \lambda_{jm}^{SC*SD} + \lambda_{kl}^{PE*G} + \lambda_{km}^{PE*SD} + \lambda_{lm}^{G*SD}$$

(equation 6.6)

where f_{ijklm} individual cell frequencies

μ constant

λ_i^{Att} main effect due to attainment

λ_j^{SC} main effect due to social class

λ_k^{PE} main effect due to parents' education

λ_l^{G} main effect due to gender

λ_m^{SD} main effect due to social disadvantage

λ_{ij}^{Att*SC} interaction between attainment and social class

λ_{ik}^{Att*PE} interaction between attainment and parents' education

λ_{il}^{Att*G} interaction between attainment and gender

λ_{im}^{Att*SD}	interaction between attainment and social disadvantage
λ_{jk}^{SC*PE}	interaction between social class and parents' education
λ_{jl}^{SC*G}	interaction between social class and gender
λ_{jm}^{SC*SD}	interaction between social class and social disadvantage
λ_{kl}^{PE*G}	interaction between parents' education and gender
λ_{km}^{PE*SD}	interaction between parents' education and social disadvantage
λ_{lm}^{G*SD}	interaction between gender and social disadvantage
i	attainment category (i=1,2,3)
j	social class category, (j=1,2,3)
k	parents' education category, (k=1,2,3)
l	gender category, (l = 1,2)
m	social disadvantage category, (m=1,2)

Although in mathematical theory there is no distinction between response and explanatory variables, the interest in this analysis lies in the effects of social class, parents' education, gender and social disadvantage on attainment at the different ages. The model can be altered to provide this information. Two way interaction terms in the standard log linear model (equation 6.6) were replaced by the appropriate ordinal interaction terms, i.e. a linear by linear association or a row effects interaction (table 6.2), and then the resulting parameter estimates are interpreted to describe the associations between pairs of factors. Non significant interactions in the standard model (equation 6.6) were also removed. The resulting ordinal log linear model (equation 6.7) is fitted to the data using SPSS. The procedure for log linear analyses for both standard and ordinal models is described in detail by Norusis (2003).

Table 6.2 Replacement ordinal terms for two way interactions in equation 6.6

Standard Interaction (equation 6.6)	Ordinal interaction (equation 6.7)
λ_{ij}^{Att*SC} *	$\beta(a_i-\bar{a})(c_j-\bar{c})$
λ_{ik}^{Att*PE} *	$\beta(a_i-\bar{a})(p_k-\bar{p})$
λ_{il}^{Att*G} *	$\alpha_l\,(a_i-\bar{a})$
λ_{im}^{Att*SD} *	$\alpha_m(a_i-\bar{a})$
λ_{jk}^{SC*PE} *	Unchanged
λ_{jl}^{SC*G}	Removed
λ_{jm}^{SC*SD} *	Unchanged
λ_{kl}^{PE*G}	Removed
λ_{km}^{PE*SD} *	Unchanged
λ_{lm}^{G*SD}	Removed

* interaction significant at α=0.05

The (reduced) ordinal model is;

$$\ln(f_{ijklm}) = \mu + \lambda_i^{Att} + \lambda_j^{SC} + \lambda_k^{PE} + \lambda_l^{G} + \lambda_m^{SD} + \beta_1(a_i-\bar{a})(c_j-\bar{c}) + \beta_2(a_i-\bar{a})(p_k-\bar{p})$$

$$+\alpha_l(a_i-\bar{a}) + \alpha_m(a_i-\bar{a}) + \lambda_{jk}^{SC*PE} + \lambda_{jm}^{SC*SD} + \lambda_{km}^{PE*SD}$$

(equation 6.7)

where β_1 = coefficient of association between attainment and social class

β_2 = coefficient of association between attainment and parents' education

α_l = coefficient of association between attainment and sex

α_m = coefficient of association between attainment and social disadvantage

a_i = known attainment values $\quad$ $\bar{a}$ = mean attainment value

c_j = known social class values $\quad$ $\bar{c}$ = mean social class value

p_k = known parental interest values $\quad$ $\bar{p}$ = mean parental interest value

all other terms as for equation 6.6

As expected, model fit (table 6.3) deteriorates between the full two way interaction model (equation 6.6) and the ordinal interactions model (equation 6.7) as the number of parameters being estimated is reduced and hence the degrees of freedom increases. In choosing a model, preference is usually given to the simplest model that provides a reasonable fit and it is not unusual to sacrifice some goodness of fit in choosing a model with fewer parameters over a more complicated model if it leads to easier and more meaningful interpretation of the analysis results (Menard 1995, Upton 1991).

Table 6.3 Goodness of fit for model 1 (equation 6.6) and model 2 (equation 6.7)

		Likelihood Ratio	Df	P
Age 5	Standard Log linear model with all 2 way interactions (equation 6.6)	73.94	74	.480
	Ordinal model (equation 6.7)	117.26	87	.016
Age 10	Standard Log linear model with all 2 way interactions (equation 6.6)	82.34	74	.237
	Ordinal model (equation 6.7)	164.27	87	.100
Age 16	Standard Log linear model with all 2 way interactions (equation 6.6)	66.40	74	.723
	Ordinal model (equation 6.7)	103.20	87	.113

The ordinal models provide a good fit for the data at ages 10 and 16 with significance level 0.05. At age 5 model fit is not as good but is still statistically significant (with significance level 0.01) and this is considered to be acceptable particularly as it can be difficult to obtain good fit with large sample sizes. For the aims of this analysis, the ordinal model is superior to the standard log linear model as it is more parsimonious and easier to interpret which is a particular benefit when dealing with variables with more than two categories.

Examination of plots of residuals (appendix 6) also indicates that the models are a good fit for the data.

6.5 Interpretation of parameter estimates

The ordinal log linear model used here (equation 6.7) allows the associations between attainment and the other social background factors to be estimated. By using the same model to analyse data at each time point then parameter estimates can be compared from one occasion to the next to gain some understanding of how the effects of social background factors change and develop over time, i.e. from one follow up to the next. The parameter estimates for these associations are shown in table 6.4 (Full results of log linear analyses are given in appendix 6). The significance of interaction terms in a log linear model is determined by examining parameter estimates and confidence intervals. Confidence intervals that include 0, (as $\ln(1) = 0$), indicate that the interaction term is not significant.

The parameters β_1 and β_2 describe the association between two ordinal factors, in this case between attainment and social class and between attainment and parents' education. These can be interpreted as estimates of the log odds of falling into the higher rather than the lower attainment band for any two categories of attainment associated with a unit increase in social class (or parents' education). For nominal factors, gender and social disadvantage, the parameter estimates α_i represent the effects of the non baseline (female and socially disadvantaged respectively) on educational attainment. Estimates of $\alpha_i > 0$ indicate an increased probability of higher categories of attainment than would be expected under independence (i.e. there is a tendency towards the higher end of the scale). Conversely $\alpha_i < 0$ indicate that lower attainment is more likely.

Table 6.4 Parameter estimates of ordinal interactions (in equation 6.7)

	Pm. Est	95% CI	ln (pm. est)
Age 5	-		-
β_1 - effect of social class	.276*	(0.224, 0.322)	1.32
β_2 - effect of parents' education	.340*	(0.282, 0.366)	1.40
α_1 – gender effect	-.226*	(-0.262, -0.168)	0.80
α_2 – effect of social disadvantage	.577*	(0.643, 0.436)	1.78
Age 10			
β_1 - effect of social class	.414*	(0.338, 0.446)	1.52
β_2 - effect of parents' education	.472*	(0.399, 0.492)	1.60
α_1 – gender effect	-.041	(-0.066, 0.029)	0.96
α_2 – effect of social disadvantage	.349*	(0.394, 0.272)	1.42
Age 16			
β_1 - effect of social class	.384*	(0.321, 0.446)	1.47
β_2 - effect of parents' education	.506*	(0.455, 0.556)	1.66
α_1 – gender effect	.081*	(0.140, 0.022)	1.08
α_2 – effect of social disadvantage	.154*	(0.072, 0.236)	1.17

* significant at $\alpha = 0.05$

The baseline (or reference category) for these models is girls with below average achievement from the semi & unskilled social class, whose parents have no formal qualifications and who have experienced some degree of additional social disadvantage.

Gender

Attainment between boys and girls differs significantly at ages 5 and 16. At age 5 the odds ratio for girls compared to boys at age 5 is calculated as exp(-.226) = 0.8 which can be interpreted as girls being 0.8 times more likely to fall into the higher attainment band rather than the lower band for any successive attainment band pairings than boys. In other words boys are (1/0.8 =1.25 times) more likely than girls to achieve above average rather than average scores and, similarly, average rather than below average scores. Towards the end of primary education at age 10 this gap has all but disappeared and there is no significant difference in attainment between the sexes. During secondary education girls appear to make more progress than boys and by the end of compulsory education, girls are just slightly more likely (1.08 times) more likely to reach a higher attainment band than boys, i.e to achieve between 1 and 4 O level passes rather than none and similarly to achieve 5 or more O level passes rather than fewer.

Social class

At all ages there is a significant association between attainment and social class. At age 5 children from any social class group are exp(0.276) = 1.32 times more likely to achieve a higher attainment band than those in the next (more deprived) social class group. For example a child from a professional background is 1.32 times more likely to achieve an above average score rather than an average score than a child from a skilled background. As the model estimates one overall association term this estimate applies to all comparisons between any four adjacent cells relating to attainment and social class, for example the group of four cell highlighted in figure 6.3.

	Attainment		
Social class	Below average	Average	Above average
IIIM, IV & V (semi & unskilled)			
II & IIINM (managerial and skilled)			
I (professional)			

Figure 6.3

By age 10 the class gap has increased so that a child from a professional background is 1.52 (exp 0.414) times more likely to achieve a score in the next higher attainment band than a child from a skilled background, and similarly for a child from a skilled background compared to a semi or unskilled background. By the end of compulsory education at age 16 the attainment gap between classes has decreased very slightly, although the higher social classes are still 1.47 (exp 0.384) times more likely to achieve scores in the next higher attainment band than that of the next (more deprived) social class group. Overall it can be concluded that the gap in attainment between different social class groups is already evident in the very early learning stages and would appear to be established in the pre-school years. The class gap in attainment is not eliminated during primary education, but in fact widens during this time. However the attainment gap decreases only slightly between the end of primary education and the end of compulsory education at age 16 which might suggest that something is working in favour of the more deprived classes during secondary education, but it is a small effect.

Parents' Education

Parents' educational attainment is an important factor in predicting children's educational prospects. Those whose parents have some qualifications or who are educated to degree level are more likely to be educationally successful, reaching the higher attainment bands. The effect is present on starting school at age 5, children whose parents' have qualifications are more likely to be in the average and above attainment band than those whose parents have no qualifications. On average the children of parents with educational qualifications are 1.40, 1.60 and 1.66 times more likely to fall into a higher attainment than children whose parents have no qualifications (at ages 5, 10 and 16 respectively). As for social class these figures apply to all combinations of attainment and parents' education. The positive association between childrens' attainment and parents' education exists at the earliest stages of education and appears to increase in strength throughout primary and secondary education.

Social Disadvantage

The social disadvantage factor indicates that disadvantage over and above that due to social class alone does have a negative impact on educational attainment. Children who have experienced some additional disadvantage are less likely to fall into the higher attainment bands than those who have not. The effect is strongest at age 5 with non-disadvantaged children being 1.8 times more likely to fall into a higher attainment band than those who have had some sort of additional disadvantage. The impact of disadvantage weakens throughout primary and secondary education with the non disadvantaged group being 1.4 and 1.17 times more likely to achieve a higher attainment level than the disadvantaged group at ages 10 and 16 respectively. Overall disadvantage factors appear to have a significant impact on attainment over and above that due to social class but the impact of disadvantage lessens over time.

6.5.1 Overall Odds Ratios

Odds ratios can be used to measure the probability of an observation appearing in one cell of a contingency table compared to the probability of it appearing in another cell and provide an indication of the strength and nature of any associations that exist.

Calculation of odds ratios for high dimension contingency tables is complex. The parameter estimates obtained from an appropriate log linear model can be used to calculate odds ratios between combinations of factors in a model. These can then be interpreted as the odds of falling into one cell compared to another for a given set of social and personal characteristics, or compared to the baseline categories (Gilbert 1993). For example, to find the odds of child A attaining 5 or more O levels compared to child B where child A is a male from the professional social class, with at least one parent educated to degree level and child B is also a male but comes from the semi & unskilled class and has parents with no qualifications, and neither have any social disadvantage is calculated as :

$$\ln\left(\frac{f_{ijklm}}{f_{iyzlm}}\right)$$

where $i=3$: attainment at level 3 ($\geq$ 5 O levels)

$j=3$: social class at level 3 (professional – child A)

$y=1$: social class at level 1 (semi & unskilled – child B)

$k=3$: parents' education at level 3 (degree – child A)

$z=1$: parents' education at level 1 (no academic qualifications – child B)

$l=3$: gender at level 1 – baseline (male)

$m=3$: social disadvantage at level 1 baseline (no disadvantage)

Using the parameter estimates from equation 6.7 (see appendix 6), this is calculated as

$$= \frac{\ln(4.178 - 3.122 - 0.634 + 5.078 + 0.081 + 0.223)}{\ln(4.178)} = 5.08$$

Therefore the odds of child A attaining 5 or more O level passes compared with child B is 5.08 or in other words the child A is 5 times more likely to attain 5 or more O level passes than child B.

6.6 Discussion of log linear modelling

The results reflect reported trends in attainment between boys and girls and show that while girls are behind boys on starting school they catch up during primary education and then girls make more progress than boys to a point where they are outperforming boys at the end of compulsory education. While education trends have altered between the sexes, trends between the social classes do not seem to have changed much. Children from more advantaged backgrounds are more likely to achieve the higher levels of attainment throughout compulsory education. The differences in average attainment between the classes are already established at age 5 and increases as children progress through primary education. During secondary education the gap decreased very slightly. The findings here would suggest that the education system does little to eradicate class inequalities in attainment overall. In fact the attainment gap between classes widens during primary education. However, the results indicate a slight decrease in social class differences during secondary education which would suggest that something is working in favour of the more deprived classes during this stage of the education system.

Again the results here agree with existing research which reports that parents' educational attainment is an important factor in children's attainment. Those whose parents have some qualifications or who are educated to degree level are more likely to be educationally successful, reaching the higher attainment bands. The positive association between childrens' attainment and parents' education exists at the earliest stages of education and appears to increase in strength throughout primary and secondary education. The results also show that social disadvantage over and above that due to social class alone has a negative impact on early educational attainment. While disadvantage continues to have an effect throughout compulsory education the impact weakens throughout primary and secondary education.

In summary the results obtained from log linear analyses again show that social inequalities in educational attainment are present throughout compulsory education. A strong association between education and social background factors is already established at the beginning of the education system when children were aged 5. This would indicate that homelife and influences in the early pre-school years are important in establishing attitudes and aspirations towards education that are likely to affect future educational success or failure which concurs with existing research (Gillborn & Mirza 2000, Joshi et al. 1999). The real value of the findings from log linear modelling here is that they provide an insight into the changing nature of the relationships between attainment and social background over time. Particularly notable is the increasing trend of higher attainment in the non-disadvantaged group compared to the disadvantaged group as time progresses. These analyses have shown that data from longitudinal studies such as BCS70 make it is possible to examine the effects of the same explanatory factors on attainment at successive time points and then directly compare findings at successive occasions to determine how associations between factors develop and change over time. The findings support the proposal that data from longitudinal studies could play an important and valuable role in the investigation of educational progression and development.

The application also shows that log linear modelling is a suitable technique for the analysis of categorical education outcomes, particularly in investigating social effects as much social background data is also categorical. In situations where the educational outcome is a true categorical variable, for example number of 'O' level passes or an ability rating, log linear and other logit models are preferable and more statistically correct than techniques based on normal or other continuous distributions. Log linear models are particularly useful when the outcome variable has more than two categories. A further advantage is that the models are readily available in most statistical software packages and so could easily be employed in education research.

Ordinal log linear models as shown here are particularly useful in the type of investigation undertaken as they account for the ordinal nature of both outcome and explanatory variables. As with all modelling, some assumptions must be made, for example the linear by linear association model assumes equal spacing of categories but this is common in many modelling techniques. Ordinal log linear models are most useful because they provide parameter estimates that can be interpreted as odds ratios which are meaningful and describe the nature and magnitude of social background effects.

While log linear modelling has proved useful here, there are some disadvantages to the technique. A drawback of this approach is that expansion of models to include many factors quickly leads to the models breaking down due to zero cells in the associated contingency table. Even with the large sample size used here, variables with low count categories such as ethnic group cause sparseness in cell counts and the statistical theory and tests used in the log linear process can become unstable. Log linear modelling is also affected by sample size. While large sample sizes require more complicated models to get a good fit than small sample sizes, at the same time some statistically significant associations found with large sample sizes may be weak and unimportant in reality.

Finally the analyses again highlight the lack of consistency between educational outcomes in BCS70 data over time. For the log linear analyses here test scores at ages 5 and 10 which were measured on continuous scales were converted to an ordered categorical scale. Converting data in this way is not ideal as much information is lost (see chapter 8). However, if suitable data were available at all measurement occasions then log linear modelling would provide a valid and meaningful method of interpreting the data.

Chapter 7 : A multinomial logistic model for ordinal education outcomes.

7.1 Introduction to modelling ordinal education outcomes in BCS70

The education measures collected throughout the BCS70 study illustrate how a variety of different scales are used to measure attainment, and how these scales change at different points in the education system. Details of post compulsory educational attainment were collected at the 1996 BCS70 follow up when the study members were aged 26. From the information available it is possible to determine the highest level of educational qualification attained by age 26 for the majority of respondents and, for analysis purposes, it is assumed that they would have completed their formal education by this time (section 3.1). The outcome is an ordered categorical variable and can be considered sequential as, usually, each lower level is attained before progressing onto the next higher level.

Categorical education outcomes are common, particularly when attainment in post compulsory education is being measured. Such measures of attainment are commonly polytomous, having more than two categories, and, furthermore, they are usually ordered. These facts should be accounted for in statistical modelling of the data and suitable analysis techniques should be used. While the ordinal log linear models, presented in chapter 6, can provide a suitable method for analysing some ordinal categorical outcomes, they are limited. As the number of outcome categories increases the models quickly become complex and interpretation of results becomes complicated. Ordinal logistic regression models can provide more appropriate methods for the analysis of multiple category ordered outcomes (Scott et al. 1997). However, while these models are quite commonly used in social science research they are not widely used in the education field.

The aim of the analyses detailed in this chapter is to investigate suitable ordinal logistic regression models for investigating data on post compulsory educational attainment collected at the 1996 BCS70 follow up study. The analysis focuses on one particular ordinal logistic method, the continuation ratio model which is not currently widely used in education research but has much potential in the field. The technique is used to examine the effects of social background (the same social factors investigated previously are used) on the highest level of educational attainment achieved at age 26. The associations between such factors and progression through the various post compulsory levels of the education system are also investigated.

7.2 Logistic Models

Logistic models belong to the group of Generalised Linear Models and are suitable for modelling categorical outcomes. There is some similarity between multinomial logistic models and log linear models (chapter 6) in that the log odds of falling into a particular response category, for individuals with a particular set of characteristics is of interest. Both models can be used to estimate the probability of falling into a particular cell (response category) using a linear function of significant explanatory variables. However, in contrast to log linear models a logistic model does distinguish between a response variable and explanatory variables (Agresti 1984). Similarly to multiple linear regression, logistic regression can be considered as modelling the combined effects of a set of explanatory variables on an outcome variable, (rather than explaining associations between variables as in log linear models).

The simplest form of the logistic model is that for a dichotomous outcome modelled against one or more explanatory variables. The technique models the probability, p, of the observation falling into one response category rather than the other; it follows that the probability of not falling into this response category is $1-p$. A transformation of p in the form of the log odds (equation 7.1), i.e. ln (the odds of falling into one category of the outcome rather than the other) is modelled as a linear function of the explanatory variables. This outcome is known as the logit of p (or the logistic transformation of p). Modelling of p differs from modelling continuous responses as the responses are in effect proportions bounded to values between 0 and 1 (Plewis 1997); hence the assumed probability distribution of the outcome and error terms is binomial (Everitt & Dunn 2001). The logit of p is modelled as :

$$\ln\left(\frac{p}{1-p}\right) = \beta_0 + \sum_i \beta_i x_i \qquad \text{(equation 7.1)}$$

where $p =$ probability associated with the outcome of interest (i.e. of falling into one category rather then the other)

β_0 = intercept

β_i = parameter estimate associated with explanatory variable i

x_i = explanatory variable i

i= 1,..,n where there are n explanatory variables

The parameter estimates obtained from a logistic regression analysis can then be used to calculate probabilities, p, and hence the associated odds of falling into one category of the response rather than the other, based on the individual values for the explanatory variables in the model (equation 7.2), as illustrated in section 7.3.3.

$$p = \frac{\exp\left(\beta_0 + \sum_i \beta_i x_i\right)}{1 + \exp\left(\beta_0 + \sum_i \beta_i x_i\right)} \qquad \text{(equation 7.2)}$$

7.2.1 Logistic models for multinomial and ordinal responses

The dichotomous models extends readily to allow modelling of categorical outcomes with more than two categories – multinomial logistic models. There are several variations of these models depending on the nature of the outcome variable under investigation. Where there is no order to the outcome (i.e. the response is nominal) then the method is called nominal, multinominal or polytomous logistic regression (Olsen 1998). When the multiple categorical outcome has some sort of rank or order attached to it, ordinal logistic models are suitable.

The educational attainment outcome being investigated here is the highest level of educational attainment achieved by age 26 (see section 4.2.4). This is measured on an ordinal categorical scale ranging from no qualifications to a degree and higher level qualifications. Clearly the outcome is ordered and so this should be accounted for in the choice of model; hence an ordinal logistic model is appropriate. More generally, categorical educational outcomes usually have some sort of inherent order to the categories and models that account for this are usually the best choice for statistical analysis of such data.

Ordinal logistic models are modifications of the standard model where the response is ordered with probabilities ($p_1, p_2, \ldots\ldots, p_c$) for c response categories. Logits are formed so as to take account of the category order, by grouping categories that are contiguous on the ordinal scale. There are three main types of multinomial logistic models that account for ordered categories of the outcome variable, the adjacent categories (AC) model, the cumulative odds (CO) model, (also known as the proportional odds model) and the continuation ratio (CR) model. Which is used depends on the meaning of the response variable and how well it fits to the model criteria.

The AC model (equation 7.3) fits separate logits on subsets of data and compares two adjacent categories at a time, in effect predicting the log odds of being in category j versus category j +1, for all adjacent combinations of the ordered outcomes. It does not account for any cumulative effect in the ordinal outcome categories where movement between categories can be considered as survival from one stage to the next.

$$\log\frac{p(Y = y_j)}{p(Y = y_{j+1})} = \beta_0 + \sum \beta_i x_i$$

(equation 7.3)

However, in education, individuals normally achieve each sequential level of educational attainment before progressing to the next level and can only progress up the scale, in effect 'surviving' or not the transition between attainment levels. For example students normally gain GCSE's (or GCE 'O' levels / CSE in BCS70) before taking A levels, then having gained A levels (or equivalent) would they go on to take a degree. Hence, models that do account for the cumulative aspect of the outcome variable are more appropriate to the outcome being investigated here.

Both the cumulative odds model and the continuation ratio model are based on cumulative logits and are appropriate where the outcome variable is measured on a true ordinal scale (Menard 1995) as it is here. While either model will use all categories of the response variable in the modelling process, which is more appropriate depends on the aim of the investigation.

As a general rule the cumulative odds (CO) model calculates cumulative probabilities of the event ($Y = y_j$). In effect the model predicts the log odds of a response in categories higher than j rather than in categories j and lower (equation 7.4). However, the model assumes that the ordinal response categories are equally spaced and that there is a 'continuous distribution' underlying the categorical response (Agresti 2002, Halpin 2003). These assumptions are not wholly realistic for the outcome being investigated here.

$$\log\frac{p(Y \le y_j)}{p(Y > y_j)} = \beta_0 + \sum \beta_i x_i \qquad \text{(equation 7.4)}$$

The continuation ratio (CR) model (equation 7.5) was first introduced by Feinberg & Mason (1979) and Feinberg (1980). It is similar to the cumulative odds model except that at each transition between outcome categories subjects in the lower categories are excluded from the analysis. The method uses successive logits to model the ratio of survival probability from one category of the outcome to the next as a linear function of main effects and interactions between a set of explanatory variables (Dos Santos & Berridge 2000). This also means that movement between categories can occur in one direction only.

$$\log\frac{p(Y = y_j)}{p(Y > y_j)} = \beta_0 + \sum \beta_i x_i$$

(equation 7.5)

Hence, the CR model is suitable for modelling ordinal outcomes where transitions between outcome categories can be considered as a series of progressions from a common starting point and where each stage must be achieved before progressing further up the scale. It provides an ideal methodology for sequential but not necessarily equally spaced ordinal outcomes where each category of the response can be considered discrete rather than as groupings on a continuous measurement scale, for example highest educational qualification achieved. Plewis (1997) gives the following guidelines for choosing between the cumulative odds and continuation ratio models for educational outcomes:

> *'Use cumulative odds when it is possible for students to move up and down the 'outcome' scale over time'.*
>
> *'Use the continuation odds when students can only move up the continuation scale'.*

To some extent, the CR model can be considered as a series of dichotomous logistic regressions modelled simultaneously (Gayle 1996, Berridge 1992a) on an appropriately structured dataset. To fit the CR model, data must first be partitioned into a series of observations relating to transitions between states of the outcome variable (Berridge 1992a, Harmon & Berridge 2000, McGowan et al. 2000, Cox 1988). At each partition a (sequentially) smaller set of individuals is 'likely' to progress to the next category because with successive logits, outcomes at lower levels are discarded. The partitions are sequential and where there are k outcome categories, k-1 partitions are needed.

For example, consider an outcome variable with ordered categories c_1, c_2 and c_3 where c_1 is the natural baseline and an individual must have progressed through category c_1 in order to reach c_2 and similarly have progressed through categories c_1 and c_2 to reach c_3. There are 3 categories and therefore 2 partitions. The first partition compares the proportion of individuals with response c_1 with those in the remaining categories c_2 and c_3. The second partition compares the proportion of individuals with response c_2 with those in category c_3; individuals in category c_1 are excluded. The partitioned data can then be fitted as a logistic model where partitioning is taken into account in the modelling process. Subsequently, parameter estimates obtained from the modelling procedure allow the effects of explanatory variables on progression from one category of the outcome variable to the next to be examined. Further detailed descriptions of the ordinal logistic models discussed can be found in Agresti (2002), Cole & Ananth (2001), Ananth & Kleinbaum (1997), Scott et al. (1997), Berridge (1992a), Winship & Mare (1984) and McCullagh (1980).

7.3 Application of the CR model to BCS70 data

The outcome variable in the following CR analysis is the highest level of educational qualification achieved by the BCS70 cohort by age 26. Study members are categorised according to the highest level of educational qualification they had achieved by age 26, derived from responses collected at the 1996 follow up study. The ordered response categories (table 7.1) represent increasing levels of educational attainment, normally achieved at successive key points in the education career. The natural baseline in this instance is no qualifications or fewer than 5 GCE'O' level passes, and movement between categories can only occur in one direction as individuals can only remain as they are or move up the attainment scale by gaining further qualifications as they progress through the education system. The outcome categories are sequential whereby an individual would normally progress through each of the lower states before achieving a higher state. The categories are distinct, i.e. an individual can only fall into one of the categories, and ordered but not necessarily equally spaced, for example, the difference between GCE O levels and A levels cannot be equated to, say, the difference between A levels and a degree. Hence the conditions for using the continuation ratio model are satisfied.

Table 7.1 Highest educational attainment in BCS70

Highest educational qualifications achieved	**N**	**Percent**
Fewer than 5 GCE 'O' level passes at grades A-C *(includes no formal educational qualifications)*	3447	47.7
5 or more GCE 'O' level passes at grades A-C *(includes, GCE O level A-C, CSE grade 1, GCSE A-C Scottish O grades A-C, Scottish standard grades A-C)*	1066	14.8
GCE A level *(at least one A level pass or HE cert / Dip.)*	1163	16.1
Degree or post graduate qualification *(Degree, MSc. MA, PhD etc.)*	1546	21.4
Total	7222	

(N.B. For the purpose of modelling the outcome variable is collapsed from six (table 4.7) to four categories (table 7.1) in order to avoid low outcome frequencies. Only respondents with full data on all explanatory variables are included)

The CR model is applied here to investigate associations between the outcome variable 'highest level of attainment' and explanatory variables representing social background factors; gender, ethnic group, social class, parents' education and social disadvantage (as defined in chapter 6). All explanatory variables are categorical and some have been collapsed to fewer categories to enable interpretation and model fit (appendix 7). The modelling procedure is carried out using the software package SABRE 3.1 (Software for the Analysis of Binary Recurrent Events), which was created as part of the ALCD (Analysis of Large and Complex Datasets) project at the Centre for Applied Statistics (CAS), University of Lancaster. The CR model illustrated here is a simple formulation of the model where the outcome variable is measured at one time point. As such this application could be modelled using most standard statistical software if the dataset is restructured to reflect partitioning of the outcome variable and this is accounted for in the modelling process (Snedker et al. 2002, Cole & Anath 2001, Bender & Benner 2000, McGowan et al. 2000, Gayle 1996).

7.3.1 Model fitting

The analysis here is similar to illustrations of the continuation ratio model outlined by Cole & Ananth (2001) and Gayle (1996). The first step is to partition the data using the *ORDINAL* command in SABRE. This creates a binary outcome variable and a partition variable which is included as an explanatory factor in the model.

The first partition compares those who had achieved < 5 GCE 'O' level passes (or equivalent) with those who gained a higher level of attainment by age 26.

The second partition compares 5 or more GCE 'O' level passes (or equivalent) with those who had achieved A levels or a HE qualification (those with fewer than 5 'O' level passes are excluded).

The third partition compares those who had achieved at least one GCE A level (or equivalent) against those who had gained a degree (those who have no qualifications higher than 'O' levels are excluded).

For each partition the probability, p_j, of an individual being in response category j, given that he/she is in category j or higher can be represented as

$$\ln\left[\frac{p_j}{\sum_{j+1}^{k} p_l}\right] = \beta_j + \sum \beta_i x_i \qquad \text{(equation 7.6)}$$

where p_j : probability of individual being in response category j

β_j : intercept or cutpoint (different for each partition)

β_i : parameter estimate associated with explanatory variable r

x_i : denotes explanatory variable r

l = 1, ..., k. as there are k categories of the outcome

$j \leq$ k

A standard logistic model (equation 7.7) with main effects for all explanatory variables (including the partition factor) is fitted initially using the SABRE *lfit* command. The default error distribution is the binomial which is appropriate here.

$$\log\left[\frac{p_j}{\sum_{j+1}^{k} p_l}\right] = \beta_j + \beta_1^{G} x_1 + \beta_2^{Eth} x_2 + \beta_3^{SC} x_3 + \beta_4^{PE} x_4 + \beta_5^{SD} x_5 + \varepsilon$$

(equation 7.7)

where p_j = probability of attainment level j

$\sum_{j+1}^{k} p_l$ = probability of attainment in level j +1 or higher

k = no. of categories attainment, 1,..,4

β_j = cutpoint

β_1^G = main effect due to gender

β_2^{Eth} = main effect due to ethnic group

β_3^{SC} = main effect due to social class

β_4^{PE} = main effect due to parents' education

β_5^{SD} = main effect due to social disadvantage

x_i = explanatory variable i = 1,..,5

ε = random term (binary)

A backward elimination approach is used to eliminate non-significant factors from the model using a standard 5% significance level. The parameter estimates obtained from this initial main effects model (see results of SABRE analysis in appendix 7) indicate that gender and social disadvantage are not significant (α=5%) factors on the highest level of educational qualification attained by age 26. All remaining explanatory factors are significant at the 5% level. The model is refitted without factors gender and social disadvantage resulting in a change in deviance of 4.04 on 2 df , indicating that there is no significant deterioration in model fit.

The main effects model assumes that the effects due to the explanatory variables, i.e. the β_i parameters, are the same across all partitions. Hence only one coefficient is calculated for each level of each explanatory variable and this applies across all partitions of the outcome variable. In reality it is possible that the effects of explanatory variables will vary between progressions, i.e. between transitions from one level of attainment to the next (Dos Santos & Berridge 2000, Gayle 1996). In order to test this assumption interaction terms between cut-points and each of the explanatory variables (i.e. cutpoint* ethnic, cutpoint*social class and cutpoint * parents' education) are introduced into the model. Only one of these terms results in a significant improvement in model fit (table 7.2), indicating that the model is improved by including this term. Interactions between cutpoint and ethnic group and between cutpoint and parents' education are subsequently removed from the model.

Table 7.2 Model fits on adding cut point interaction terms

	Deviance	Df	Change in deviance	Change in df
Main effects model *(includes factors ethnic group, social class and parents' education)*	16744.42	13698		
Main effects + (cutpoint * ethnic group)	16742.97	13696	1.45	2
Main effects + (cutpoint * social class)	16702.10	13694	42.32**	4
Main effects + (cutpoint * social class) + (cutpoint * parents' education)	16688.74	13690	13.36	4

** *change in deviance significant at* $\alpha = 0.05$

As interaction terms for the effects of ethnic group and parents' education were not significant it can be assumed that the single parameter estimate for these variables can be applied across all partitions of the outcome variable. Hence the best fitting model for the data was found to be

$$\log\left[\frac{p_j}{\sum_{j+1}^{k} p_l}\right] = \beta_j + \beta_2^{Eth} x_2 + \beta_3^{SC} x_3 + \beta_4^{PE} x_4 + \beta_6^{Cut*SC} x_6 + \varepsilon$$

(equation 7.8)

where β_5^{Cut*SC} = interaction between cut point and social class

x_6 = cutpoint * social class

(all other terms as for equation 7.7)

7.3.2 Interpretation of results

The final model (equation7.8) includes significant main effects due to ethnicity, social class and parents' education. The analysis has shown that the effects due to ethnic group and parent's education are the same at all three partitions of the outcome variable, i.e. at all transitions from one level of attainment to the next higher level. The effect due to social class differs depending on the point of transition in the hierarchical order of level of attainment. Interpretation of the results of the modelling process is not straightforward and it is usually best to explain the parameter estimates for each explanatory variable separately.

In general, the cutpoint estimates, β_j, represent the log continuation ratios of a baseline individual having a response in category j rather than in categories j+1,...,k] (Berridge 1992a). They may be interpreted as the log odds of a response in category j rather than a higher category at each of the three partitions. For example, at partition 1, the cut point parameter estimate represents the log odds of having fewer than five GCE passes compared to having gained at least five GCE passes[1].

The parameter estimates of β_i, (table 7.3) are the main figures of interest in this type of analysis as they represent, for each explanatory variable, the log odds of an individual falling into the lower educational attainment level rather than the higher attainment level.

[1] It is noted that the cut point estimates for partitions 1 and 3 have large standard errors, This indicates much variation between individuals and is probably due to the range of educational attainment levels grouped within each outcome category.

Table 7.3 Parameter estimates obtained from preferred CR model.

Parameter	Estimate, β_I (log odds)	Standard error	Sig	exp (β_i)
Baseline				
Cut point (1)	-0.04	0.12		0.96
Cut point (2)	-0.93	0.12		0.39
Cut point (3)	-0.12	0.13		0.89
White (U.K.)	0.86	0.11	*	2.36
II & III NM	-0.78	0.05	*	0.46
(managerial & skilled non manual)				
I (professional)	-1.51	0.13	*	0.22
Parents have 'O' or 'A'levels	-0.51	0.05	*	0.60
Parents have a degree	-1.24	0.06	*	0.29
Cut point (2) * II & III NM	0.39	0.09	*	-0.94
Cut point (2) * I	0.90	0.19	*	2.46
Cut point (3) * II & III NM	0.37	0.10	*	1.45
Cut point (3) * I	0.79	0.19	*	2.20

In general a positive coefficient indicates an increased chance that an individual will be in the lower attainment category rather than the higher attainment category. Hence a negative coefficient indicates that an individual is more likely to fall into the higher attainment level. The parameter estimates assume equally spaced categories of explanatory variables and are calculated against the baseline category, here the baseline is an individual of non U.K origin from the semi-skilled & unskilled social class whose parents have no formal qualifications.

Social Class

The results indicate differences in attainment between social classes. The significant interaction term between cut point and social class shows further that the effect due to class is not constant across all partitions, i.e. at each transition between levels of attainment. The effects of social class on attainment and progression through the various levels of attainment are calculated as shown in table 7.4.

Table 7.4 Parameter estimates for social class effects

Cut point * Social class	Estimate	Exp (est)
>5 GCE O levels rather than Alevels or higher qualification		
* social classes IIIM, IV and V	-0.93 + 0.000	0.39
* social classes IIINM and II	-0.93 -0.78 + 0.39	0.27
* social classes I	-0.93 -1.51 + 0.90	0.21
Alevels rather than degree or PG qualification		
* social classes IIIM, IV and V	-0.12 + 0.000	0.87
* social classes IIINM and II	-0.12 -0.78 + 0.37	0.59
* social classes I	-0.12 -1.51 + 0.79	0.43

The baseline group is classes IIIM (skilled manual), IV (semi-skilled) and V (unskilled) and the results show that the more advantaged social class groups are increasingly more likely to attain the higher levels of attainment at each partition. Having gained at least five GCE O levels passes, individuals from the skilled non-manual and managerial classes (IIINM and II) are 1/0.27 = 5.4 times more likely to have obtained at least A levels than those from the lower social class groups (table 7.4). Those from the professional class (I) are (1/0.21) = 4.8 times more likely to have obtained at least A levels rather than just O levels. Similarly having gained at least A levels, individuals from the skilled non-manual and managerial classes (IIINM and II) are again 1/0.59 = 1.7 times more likely to have obtained a degree or post graduate qualification than those from the lower social class groups (table 7.4). Those from the professional class (I) are more than twice (1/0.43) as likely to have obtained a degree rather than just A levels.

Ethnicity

The results indicate that the white (U.K.) group are 2.4 times more likely to fall into the lower attainment category than the higher category for each partition, or in other words ethnic minorities are more likely to appear in the higher attainment level at each partition. This reflects preliminary findings which indicated that ethnic minority students who continued in education after the end of compulsory education. were actually more likely to reach the higher levels of attainment than whites.

Parents' Education

Individuals whose parents have some level of academic qualification, i.e. O levels or A levels (and equivalents) are (1/0.60)= 1.7 times more likely to attain the higher levels of attainment. Those whose parents have a degree are 1/0.29 = 3.5 times more likely to have higher rather than lower attainment for each partition.

7.3.3 Odds Ratios

Although interpretation of individual terms in the model can provide a useful insight into how distinct experiences might influence educational attainment, the number and complexity of parameter estimates do not always lend themselves to straightforward interpretation (Feinberg 1980, Gayle 1996). However, formulation of a statistical model with several explanatory variables allows the effects of such factors working together simultaneously to be evaluated and a more useful application of the results of such an analysis can be to in evaluation of the log odds for a particular combination of social experiences. In effect, estimating probabilities associated with reaching the various levels of educational attainment for distinct social groups, while accounting for other significant social influences.

Here, odds ratios can be calculated to obtain estimates of the probability that an individual with a given set of social background characteristics will progress to the higher attainment level, having attained the next lower level, at each partition. Odds ratios comparing individuals from different social backgrounds can also be calculated. For example, the odds that an individual A, who is from a professional background and whose parents are educated to degree level, achieves 'A levels or higher' rather than '5 or more O levels' (partition 2) given that they have achieved at least some qualifications compared with an individual, B, from the baseline category (i.e. from the semi & unskilled class, whose parents have no qualifications) can be calculated as the inverse of the logs obtained by evaluating the CR model as

$$= \frac{\ln(-0.93 + 0 + (-1.51 + 0.90) + (-1.24))}{\ln(-0.93)} = 0.16$$

Therefore individual A is (1/0.16) i.e. more than 6 times more likely to achieve A levels than individual B (n.b. both A and B belong to the baseline, non white, ethnic group). Similar odds can be estimated for individuals with different social backgrounds at each transitional level of attainment.

7.3.4 Contextualisation of results with existing research findings.

On the whole the results obtained from the CR analysis of BCS70 age 26 data agree with existing reports about the effects of social background on educational attainment. The results here show that attainment differs significantly between the social classes, with young people from the less advantaged social classes being less likely to reach the higher levels of attainment than those from the more advantaged classes. The effect increases with decreasing social class with individuals from the lower social classes being the least likely to reach the higher attainment levels. This reflects historical and current research (Gayle et al. 2002, Rudd 1987) which reports the continuing disparity in educational attainment between the various social classes, particularly at higher levels of the education system.

The results here also indicate that parental education has a significant influence on attainment, which is in broad agreement with existing research. The results show that the children of parents who achieved the higher levels of educational qualifications are more likely to attain the higher levels of educational qualification themselves. This agrees with work by Gayle et al (2002) and Burnhill et al (1990) who compared the social background of those entering Higher Education with those who did not, and identified parental education as being one of the main factors influencing Higher Education participation. Here we have shown additionally that the chances of reaching the higher levels of educational attainment increase as the level of parents' education increases, by including three distinct levels of parental education in the model rather than the more usual two, representing parents who have a degree or not.

The results obtained also indicate attainment differences between different ethnic groups. Traditionally ethnic minorities have been considered to be amongst the lowest achievers and social class differences are often cited in explanation. However, the CR model application here, controls for social class in the modelling process and subsequently the results suggest that ethnic minorities are actually more likely to reach the higher levels of educational attainment than whites. This concurs with preliminary findings from the BCS70 data (chapter 4) and with existing research which shows that ethnic minorities, particularly some groups, actually make more progress in the later stages of compulsory education than their non minority peers (Haque & Bell 2001, McNiece et al. 2004). Recent research also shows that white, U.K. born students are less likely to have a positive attitude towards higher education (Yeshanew et al. 2005). Again the ethnic grouping of white and non-white probably masks differences within the ethnic minority category. For example, research carried out at the time of the BCS70 study shows significant variation in the O level achievements of particular ethnic minority groups (Drew & Gray 1991, 1990, Brewer & Haslum 1986).

The finding that gender is not a significant factor in educational attainment concurs with some reported trends in post compulsory education, while conflicting with others. Within the BCS70 cohort there was no significant difference between the sexes in the highest level of education attained by age 26 and from this it might be concluded that males and females are equally likely to progress to the varying levels of post compulsory education. Recent research investigating post compulsory education routes also found that there was no significant difference between the sexes (Harmon & Berridge 2000) and females are reported to have a more positive attitude towards higher education than males (Yeshanew et al. 2005). Furthermore it is widely reported that the historical 'male advantage' in attainment has closed and that females now do at least as well, and often better, than males in GCSE, AS and A level examinations (Gorad et al. 2001, Arnot et al. 1999). Conversely other research reports that females are less likely to continue their education at the end of compulsory schooling than boys with similar qualifications (Yang & Woodhouse 2001), and that females are also less likely to enter higher education (Gayle et al. 2002). Overall the varying findings show that gender trends within post compulsory education are complex and require detailed investigation in order to be fully understood.

7.4 Discussion

The application of the CR model shown here is a cross sectional analysis of BCS70 data collected at a single time point in 1996. The data is retrospective and at the time of analysis there was little scope for determining additional information about when and in what order qualifications were achieved. Hence some assumptions are made in interpreting the results, particularly with respect to suggestions about progression between attainment levels. There is an inherent assumption that all study members have progressed through the education system in the standard fashion of taking O levels before taking A levels before going on to take a higher education qualification such as a degree. This is justified by the fact that the majority of individuals do still progress through the education system following this standard route, and did so in the early 1990s but it must be borne in mind that this may not be the case for every study member. More recent data collections from the BCS70 cohort (2000 and 2004) may provide more detailed educational histories for the cohort but these collections were not available at the time that this work was carried out. Further work might include determining more detailed education profiles for the cohort members if the data are available. The more recent data collections might also allow for an increase in sample size and in the number of explanatory social variables that can be investigated if some of the gaps due to missing data in earlier collections can be filled in.

However, the CR model has much wider possibilities in education research. As patterns of educational study and routes into higher education are increasingly changing, more complex ordinal and longitudinal outcomes are likely to result and hence suitable analysis techniques will be required. The CR model is applicable to such complex ordinal outcomes, particularly those found in longitudinal data where the same respondents are followed over time and will have several outcome measures recorded at different time points. For example work carried out by Harmon & Berridge (2000) uses the CR model to investigate young peoples' post compulsory education routes in a data set that monitored the educational position of 800 individuals at 3 separate yearly intervals. The nature of the CR model means that it can be used in situations where individuals may change their position between measurement occasions, as it accounts for movers, (those who move between outcome levels over time), and stayers, (those who do not change their outcome throughout the monitoring time period). For example, consider the BCS70 cohort and suppose that the cohort members had been monitored several times between the ages of 16 and 26, providing a longitudinal data set of highest educational attainment at regular intervals. The data would then be truly longitudinal and movers would be those who move between attainment categories at one or more measurement occasions. An element of time and when qualifications were achieved could then be included in the model allowing a more realistic interpretation of factors that affect progression through the different levels of educational attainment. In this instance stayers would be those who left education at age 16 and are assumed not to have participated in any further education and hence would never progress from the lowest attainment band.

As with all analyses of social background data there is some degree of relationship between explanatory variables. For example social class is usually related to parents' education. Parents with higher levels of education are usually employed in professions that fall into the more advantaged social class categories. However it is common in education research and in social science in general to consider several of these factors together while ensuring that problems of multicollinearity and endogeneity do not have a serious impact on the reliability of results. A description of collapsing and recoding variables is given in chapter 4.

Currently the CR model is more commonly used in ecological (Kvist et al. 2000) and epidemiological studies (Van Ness 2004, Cole & Ananth 2001) than in education studies. The analysis carried out here, data limitations withstanding, illustrates that the technique has much potential in the education field. It is well suited to the analysis of educational outcomes where there is a natural baseline and where movement between categories represents the natural progression through sequential levels of attainment. In particular the CR model is suitable for the investigation of educational progression where transitions between the different education stages cannot be assumed to be equal "distances" apart and where movement can only occur in one direction, for example, increasing levels of attainment. The technique is increasingly attractive as it lends itself to the analysis of truly longitudinal data which is becoming increasingly important in education research. A possible explanation for the lack of use of the technique in the past could be that the CR model is not an obvious option in the standard statistical software packages in general use. However, the model can be fitted using many of these packages including SAS (Snedker et al 2002), SPSS (SPSS Inc. 2003), GLIM (McGowan et al. 2000, Gayle 1996, Berridge 1992b) and SABRE as used here, although some manipulation of the original data is usually required.

Although ordinal logistic models have been around for some time they are not currently widely used in education studies despite the suitability of the techniques for investigating many educational outcomes. The analysis here illustrates how the CR model is an appropriate analysis tool for selected ordinal educational outcomes. Further, it makes a case for more widespread use of ordinal logistic regression models for different types of categorical educational outcomes found in education data. For example, probit models, appropriate when categories reflect an underlying normal distribution, and stereotype ordinal regression, for outcomes where the importance of order is not clear, may also be applicable to some educational outcomes. In conclusion, ordinal logistic models and particularly the CR model have much to offer in the way of statistical analysis for future education research.

Bibliography

References:

Agresti, A. (1984) *Analysis of Ordinal Categorical Data,* Wiley, New York.

Agresti, A. (2002) *Categorical Data Analysis. 2nd Edition,* Wiley, New York.

Aitken, M., Longford, N. (1986) 'Statistical Modelling Issues in School Effectiveness Studies', *Journal of the Royal Statistical Society A*, 149, (1), 1-43.

ALBSU (1993) ' The Basic Skills of Young Adults', The Adult Literacy and Basic Skills Unit, London.

Anath, C., Kleinbaum, D. (1997) 'Regression models for ordinal responses : a review of methods and applications' *International Journal of Epidemiology*, 26, (6), 1323-33.

Arnot, M., Davis, M., Weiner, G. (1999) *Closing the Gender Gap. Post-war education and social change*, Polity Press, Cambridge.

Bender, R., Benner A. (2000) 'Calculating Ordinal Regression models in SAS and S-Plus' *Biometrical Journal* 42 (6), 677-699.

Berridge, D.M. (1992a) 'A review of methods for modelling ordered categorical survey data' in Proceedings of the 21st SGCSA conference on Survey and Statistical Computing, Elsevier.

Berridge, D.M. (1992b) 'Fitting the continuation ration model in GLIM 4' in Fahrmeir, L. et al. (Eds.) *Advances in GLIM and Statistical Modelling,* Lecture notes in Statistics, 78, Springer-Verlag, New York.

Blatchford, P., Burke, J., Farquhar, C., Plewis, I., Tizard, B. (1985) 'Educational achievement in the infant school : the influence of ethnic origin, gender and home on entry skills' *Educational Research,* 27, (1), 52 – 60.

Bock, R.D. (Ed.) (1989) *Multilevel Analysis of Educational Data,* Academic Press, New York.

Bondi, L. (1991) 'Attainment in Primary Schools' *British Educational Research Journal* 17, (3), 203-217.

Brandsma, H.P., Knuver, J.W.M. (1989) 'Effects of school and classroom characteristics on pupil progress in language and arithmetic' *International Journal of Educational Research* 13, (7), 777-788.

Breen, R., Goldthorpe, J.H. (2001) 'Class, Mobility and Merit' *European Sociological Review*, 17, (2), 81-101.

Brewer, R., Haslum, M. (1986) 'Ethnicity: the experience of socio-economic disadvantage and educational attainment' *British Journal of Sociology of Education* 7, (1), 19-34.

Burnhill, P., Garner, C., McPherson, A. (1990) 'Parental Education, Social class and Entry to Higher Education 1976-1986' *Journal of the Royal Statistical Society A*, 153, (2), 233-248.

Bynner, J., Steedman, J. (1995) 'Difficulties with Basic Skills. Findings from the 1970 British Cohort Study.' Basic Skills Agency (BSA), London.

Bynner, J., Wiggins, R., Parsons, S. (1996) 'An exploratory comparative analysis of data collected in the 1958 and 1970 British birth cohort studies : The role of personal agency in entry to employment under different labour market conditions' Paper presented to the conference of the International Sociological Association Research committee on Logic and Methodology, University of Essex, July 1996.

Bynner, J., Parsons, S. (2001) 'Qualifications, Basic Skills and Accelerating Social Exclusion' *Journal of Education and Work*, 14, (3), 279-291.

Bynner, J., Joshi, H. (2002) 'Equality and Opportunity in Education: evidence from the 1958 and 1970 birth cohort studies' *Oxford Review of Education*, 28, (4), 405-425.

Campbell, J. (2001) 'The colonisation of the primary curriculum' in Phillips, R., Furlong, J. (Eds) *Education, Reform and the State. Twenty five years of politics, policy and practice,* Routledge Falmer, London.

Chatfield, C., Collins, A.J. (1980) *Introduction to Multivariate Analysis* Chapman & Hall, London.

Cohen, J. (1994) 'The Earth is round (P<0.05)' *American Psychologist*, 49, 997-1003.

Cole, S.R., Ananth, C.V. (2001) 'Regression models for unconstrained, partially or fully constrained continuation odds ratios' *International Journal of Epidemiology*, 30, (6), 1379-1382.

Copas, J.B., Li, H.G. (1997) 'Inference for Non-random Samples' *Journal of the Royal Statistical Society B* 59, (1), 55-95.

Cox, C. (1988) 'Multinomial regression models based on continuation ratios' *Statistics in Medicine*, 7, 435-441.

Craft, M., Craft, A. (1983) 'The participation of ethnic minority pupils in further and higher education' *Educational Research* 25, (1), 10-19.

Dale, A., Davies, R.B. (1994) *Analysing Social and Political Change. A casebook of methods,* Sage, London.

Davie, R (1973) 'Behaviour and adjustment in school of seven years olds: sex and social class differences' *Early child care and development*, 2, 39-47.

Despotidou, S., Shepherd, P. (2000) '1970 British Cohort Study Twenty six –year Follow-up. Guide to data available at the ESRC Data Archive', SSRU, City University, London.

Diggle, P.J., Liang, K., Zeger, S.L. (1994) *Analysis of Longitudinal Data*, Clarendon Press, Oxford.

Dobson, A.J. (1990) *Introduction to Generalized Linear Models*, Chapman and Hall, London.

Dos Santos, D.M., Berridge, D. M. (2000) 'A continuation ratio random effects model for repeated ordinal responses' *Statistics in Medicine*, 19, 3377-3388.

Drew, D., Gray, J. (1990) 'The fifth year examination achievements of black young people in England and Wales' *Educational Research* 32, (2), 107-117.

Drew, D., Gray, J. (1991) "The black white gap in examination results: a statistical critique of a decades's research' *New Community* 17, (2), 159-172.

Duncan, C., Gould, M., Jones, K., Moon, G. (1994) *Using Multilevel Models*, handbook prepared for Multilevel workshop, University of Portsmouth.

Elliot, D. (1991) *Weighting for non-response, A survey researcher's guide*, OPCS, London.

Elliot, K., Schagen, I. (2004) in Schagen, I., Elliot, K. (Eds.) *But what does it mean? The use of effect sizes in educational research*, National Foundation for Education Research (NFER) & Institute for Education, London.

Elliot, K., Sammons, P. (2004) 'Exploring the use of effect sizes to evaluate the impact of different influences on child outcomes: possibilities and limitations' in Schagen, I., Elliot, K. (Eds.) *But what does it mean? The use of effect sizes in educational research*, NFER & Institute for Education, London.

Ely, M.(1999) 'The importance of estimates and confidence intervals rather than p values' *Sociology*, 33, (1), 185-190.

Epstein, D., Elwood, J., Hey, V., Maw, J. (Eds.) (1998) *Failing Boys? Issues in Gender and Achievement* on behalf of Institute of Education, University of London, Open University Press, Buckingham.

Essen, J. (1979) 'Living in One- Parent Families: attainment at school' *Child: Care, Health and Development*, 5, (3), 83-93.

Everitt, B. S., Dunn, G. (2001) *Applied Multivariate Data Analysis, 2nd Edition*, Arnold, London.

Feinburg, S., Mason, W. (1979) 'The identification and estimation of age-period – cohort models in the analysis of discrete archival data' in Schuessler,K.E. (ed.) *Sociological Methodology*, Jossey-Bass, San Francisco, 1-67.

Feinburg, S.E. (1980) *The Analysis of Cross-classified Data*, MIT Press, Boston.

Feinstein, L. (1998) 'Pre-school Educational Inequality? British Children in the 1970 Cohort' Centre for Economic Performance, Discussion paper 404.

Feinstein, L., Symons, J. (1999) 'Attainment in secondary school' *Oxford Economic Papers*, 51, 300-321.

Fielding, A., Yang, M., and Goldstein, H.(2003) 'Multilevel ordinal models for examination grades' *Statistical Modelling*, 3, (2), 127-153.

Fogelman, K. (1984) 'Assessment of Examination performance in Different Types of schools' *Journal of the Royal Statistical Society A* 147, (4), 569-581.

Gayle, V. (1996) 'Modelling tabular data with an ordinal outcome' *Sociological Research online*, 1, (3).

Gayle, V., Berridge, D., Davies, R.B. (2000) 'Young people's routes to higher education : exploring social processes with longitudinal data' *Higher Education Review*, 33, (1), 47-64.

Gayle, V., Berridge, D., Davies, R.B. (2002) 'Young People's entry into Higher Education : quantifying influential factors' *Oxford Review of Education*, 28, (1), 5-20.

Gillborn, D., Drew, D. (1992) 'Race, Class and School effects' *New Community* 18, (4), 551-565.

Gillborn, D., Mirza, H.S., (2000) *Educational Inequality: Mapping Race, Class, Gender: A synthesis of research evidence*, OFSTED.

GLARE (1988) *Race, Equality and the Education Reform Act*, London.

Goldstein, H. (1979) 'Some Models for Analysing Longitudinal Data on Educational Attainment' *Journal of the Royal Statistical Society A*, 142, (4), 407-442.

Goldstein, H. (1986a) 'Efficient Statistical Modelling of Longitudinal Data' *Annals of Human Biology* 13, (2), 129-214.

Goldstein, H. (1986b) 'Multilevel mixed linear model analysis using iterative generalised least squares' *Biometrika* 73, (1), 43-56.

Goldstein, H. (1987) *Multilevel Models in Educational and Social Research*, Griffen & Co., London.

Goldstein, H., Healy, M.J.R., Rasbash, J. (1994) 'Multilevel time series models with applications to repeated measures data' *Statistics in Medicine* 13, 1643-1655.

Goldstein, H., Brown, W., Rasbash, J., (2002) 'Partitioning variation in multilevel models' *Understanding Statistics*, 1, 223-232.

Gorard, S., Rees, G., Salisbury, J. (2001) 'Investigating the patterns of differential Attainment of Boys and Girls at School' *British Educational Research Journal*, 27, (2), 125-139.

Gray, J. (1981) 'Towards Effective Schools: problems and progress in British research' *British Educational Research Journal*, 7, (1), 59-69.

Gray, J., Jesson, D., Sime, N. (1990) 'Estimating Differences in the Examination Performances of Secondary Schools in Six LEAs: a multilevel approach to school effectiveness. *Oxford Review of Education* 16, (2), 137-158.

Gray, J., Goldstein, H., Thomas, S. (2001) 'Predicting the future: the role of past performance in determining trends in institutional effectiveness at A level' *British Educational Research Journal*, 27, (4), 391-405.

Gray, J. (2004) in Schagen, I., Elliot, K. (Eds.) *But what does it mean? The use of effect sizes in educational research*, NFER & Institute for Education, London.

Gray, J., Peng, W., Steward, S., Thomas, S. (2004) 'Towards a typology of gender-related school effects : some new perspectives on a familiar problem' *Oxford Review of Education*, 30, (4), 529-550.

Green, J.A. (1988). 'Loglinear Analysis of Cross-classified Ordinal Data: Applications in Developmental Research' *Child Development* 59, 1-25.

Hair, J.F., Anderson, R.E., Tatham, R.L., Black, W.C. (1995) *Multivariate Data Analysis*, Prentice Hall, London.

Halpin, B., (2003) 'Multinomial and Ordinal Logistic Regression' http://teaching.sociology.ul.ie/SSS/lugano/node73.html (19/11/2003)

Halsey, A.H., Heath, A.F., Ridge, J.M. (1980) *Origins and destinations : Family class and education in modern Britain,* Claredon Press, Oxford.

Hand, D., Crowder, M. (1996) *Practical Longitudinal Data Analysis*, Chapman & Hall, London.

Harman, J., Berridge, D.M. (2000) 'Modelling young people's post-compulsory educational routes' in *Teaching Resources and Materials for Social Sciences* http://tramss.data-archive.ac.uk (03/2003)

Hatcher, R., Thomas, S. (2000) 'Equity and School Effectiveness Research' *Race, Ethnicity and Education,* 3, (1), 103-109.

Haque, Z., Bell, J.F. (2001) 'Evaluating the Performances of Minority Ethnic Pupils in Secondary Schools' *Oxford Review of Education*, 27, (3), 339-356

Heath, A.F, Clifford, P. (1990) 'Class Inequalities in Education in the Twentieth Century' *Journal of the Royal Statistical Society A* 153, (1), 1-16.

Heitjan, D.F., Landis, J.R. (1994) 'Assessing Secular Trends in Blood Pressure : A Multiplie- Imputation Approach' Journal of the American Statistical Association 89, 1-25.

HMSO (1985) *Better Schools*, HMSO, London.

HMSO (1982-1996) *Education Statistics for the United Kingdom* , HMSO, London (selected readings).

Ishii-Kuntz, M. (1994) *Ordinal log-linear models,* Sage, London.

Ives, R. (1984) 'School reports and self reports of examination results' *Survey Methods Newsletter*, Winter.

Jackson, B., Marsden, D. (1966) *Education and the working class,* Penguin, Harmondsworth.

Jesson, D. Gray, J. (1991) 'Slants on slopes: Using multilevel models to investigate differential school effectiveness and it's impact on Pupils Examination Results' QQSE Research Group, Division of Education , University of Sheffield

Johnson, R.A., Wichern, D.W. (1992) *Applied Multivariate Statistical Analysis*, Prentice-Hall, Englewood-cliffs, New York.

Jones, K. (2003) *Education in Britain 1944 to the present,* Polity Press, Cambridge.

Joshi, H., Cooksey, E.C., Wiggins, R.D., McCulloch, A., Verropoulou, G., Clarke, L. (1999) 'Diverse family living situations and child development: A multi-level analysis comparing longitudinal evidence from Britain and the United States' *International Journal of Law, Policy and the Family*, 13, 292-314.

Kalton, G. (1981) 'Compensating for Missing Survey Data' Survey Research Center, Institute for Social Research, University of Michigan.

Kalton, G. (1982) 'Imputing for Missing Survey Responses' Proceedings of the Section on Survey Research Methods, American Statistical Association .

Kvist, T., Gislason, H., Thyregod, P. (2000) 'Using continuation-ratio logits to analyse the variation of the age composition of fish catches' *Journal of Applied Statistics*, 27, (3), 303-319.

Laird, N.M. (1988) 'Missing Data in Longitudinal Studies' *Statistics in Medicine*, 7, 305-315.

Lambert, P., Gayle, V. (2004) 'Longitudinal Research in Education', one day workshop, University of York, January 23rd 2004.
http://www.cf.ac.uk/socsi/capacity/Activities/Themes/Secondary/longitudinal.html (05/2005)

Little, R.J.A., Rubin, D.B. (1987) *Statistical Analysis with Missing Data*, Wiley, New York.

Madow, W.G., Olkin, I. (1983) *Incomplete Data in Sample Surveys, Panel on Incomplete Data. Proceedings of the symposium*, Academic Press, New York.

Manly, B.F.J. (2005) *Multivariate Statistical Methods. A primer. 3rd Edition*, Chapman & Hall , London.

Marks, D.J., (1984) 'Assessment of Examination Performance in different types of Schools' *Journal of the Royal Statistical Society A* 147, (4), 569-581.

McCullagh, P. (1980) 'Regression models for Ordinal data' *Journal of the Royal Statistical Society B* 42, (2), 109-142.

McCullagh, P., and Nelder, J.A. (1989) *Generalised Linear Models, 2nd edition*, Chapman & Hall, London.

McDaniel, S., Madden, C., Verille, P. (1987) 'Do topic differences affect survey non-response?' *Journal of the Market Research Society*, 29, 55-66

McGowan, M.J.(2000) 'Ordinal outcomes with the Continuation Ratio Model' www.pace.edu/nesug/proceedings/nesug00/ps/ps7015.pdf (03/2003)

McLean, J.E., Ernest, J.M. (1998) 'The Role of Statistical Significance Testing in Educational Research' *Research in the Schools* 5, (2), 15-22.

McNiece, R., Jolliffe, F. (1998) 'An Investigation into regional differences in educational performance in the NCDS' *Educational Research*, 40, 1, 17-30.

McNiece, R. , Bidgood, P., Soan, P. (2004) 'An Investigation into using national longitudinal studies to examine trends in educational attainment and development' *Educational Research*, 46, 2, 119-136.

Menard, S. (1991) *Longitudinal Research*, Sage, London..

Menard. S. (1995) *Applied Logistic Regression Analysis*, Sage, London.

Mortimore, P., Blackstone, T. (1982) *Disadvantage and Education*, Heinemann, London.

Nisselson, H (1983) *Incomplete Data in Sample Surveys. Part II* Academic Press, New York.

Norusis, M.J. (2003) *SPSS 12.0 Statistical procedures companion*, Prentice-Hall, Englewood Cliffs, New York.

Nuttall, D.L., Goldstein, H., Proser, R., Rasbash, J. (1989) 'Differential School Effectiveness' *Journal of Educational Research*, 13, 769 – 776.

Olsen, C., (1998) 'StatNews #32: Generalisations of Logistic Regression' http://www.humna.cornell.edu/admin/statcons/. (05/ 2003)

ONS (2000) *Tracking people: a guide to longitudinal social sources*, Office for National Statistics (ONS), London.

Parsons, S., Bynner, J. (2002) 'Basic skills and Social Exclusion. Findings from a study of adults born in 1970' The Basic Skills Agency, London.

Paterson, L.(1991) 'Socio-economic status and educational attainment : A multidimensional and multilevel study' *Evaluation and Research in Education* 5, (3), 97-121.

Plewis, I. (1987) 'Social Disadvantage, Educational Attainment and Ethnicity: a comment' *British Journal of Sociology* 8, (1), 77-82.

Plewis, I. (1988) 'Assessing and Understanding the Educational Progress of Children from Different Ethnic Groups' *Journal of the Royal Statistical Society A* 151, (2), 316-326.

Plewis, I. (1993) 'Reading progress'. In Woodhouse, G. (Ed.), *A guide to ML3 for new users,* Multilevel Models Project, Institute of Education, London.

Plewis, I., (1997) *Statistics in Education,* Arnold, London.

Plewis, I., (2002) 'Modelling ordinal data using *MLwiN*' *Multilevel Modelling Newsletter* 14, 1, Economic and Social Research Council, London.

Rasbash, J., Browne, W., Goldstein., H., Yang, M. (2000). *A user's guide to MLwiN* (Second Edition). Institute of Education, London.

Raudenbush, S.W., (1989) 'The analysis of longitudinal, multilevel data' *International Journal of Educational Research*, 13, (7), 721-740.

Raudenbush, S.W., Willms,J.D. (1991) (Eds) *Schools, Classrooms and Pupils*, Academic Press, London.

Rizvi, M.H. (1983) *Incomplete Data in Sample Surveys : part IV,* Academic Press, New York.

Rubin, D.B. (1976) 'Inference and missing data', *Biometrika*, 63, (3), 581-592.

Rubin, D.B. (1987) *Multiple Imputation for Non-response in Surveys*, Wiley, New York .

Rudd, E. (1987) 'The Educational qualifications and social class of the parents of undergraduates entering British Universities in 1984' *Journal of the Royal Statistical Society A*, 150, 346-372.

Sammons, P., Nuttall, D., Cuttance, P., Thomas, S. (1993) 'Continuity of school effects: A longitudinal analysis of primary and secondary school effects on GCSE performance' Dept. of Curriculum Studies, Institute of Education, London.

Sammons, P (1995) 'Gender, Ethnic and Socio-economic differences in Attainment and Progress: A longitudinal analysis of student achievement over nine years' *British Educational Research Journal* 21, (4), 465-485.

Saunders, P. (1996) *Unequal but fair? A study of class barriers in Britain*, IEA Health and Welfare unit, London.

Schagen, I. Elliot, K. (Eds.) (2004) *But what does it mean? The use of effect sizes in educational research.* NFER and Institute of Education, London.

Schagen, I., Schagen, S. (2005) 'Combining multilevel analysis with national value-added data sets – a case study to explore the effects of school diversity.' *British Educational Research Journal*, 31, 3, 309-328.

Scott, S.C., Goldberg, M.S., Mayo, N.E. (1997) 'Statistical Assessment of Ordinal Outcomes in Comparative Studies'. *Journal of Clinical Epidemiology*, 50, (1), 45-55.

Scottish Office (The) (1996) ' Scottish Certificate of Education, Standard grade' Factsheet 5 from http://www.scotland.gov.uk/library/documents/standard.htm

Shepherd, P. (1995). *The National Child Development Study. An introduction, its origins and the methods of data collection.* NCDS user support group, working paper 1.

Smithers, A., Robinson, P. (1995) Co-education and Single sex schooling Manchester, Centre for Education and Employment Research.

Snedker, K., Glynn, P., Wang, C., (2002) 'Ordered / Ordinal Logistic Regression with SAS and STATA' http://staff.washington.edu/glynn/olr.pdf (23/6/2003)

SPSS Inc. (2003) *SPSS Advanced Models 12.0,* SPSS Inc., Chicago

St. Clair, L., Osborn, A.F., (1987) 'The ability and behaviour of children who have been 'in care' or separated from their parents. Report to the Economic and Social Research Council' *Early Child Development and Care*, 28, 187-354.

Steedman, J. (1983) 'Examination Results in mixed and Single sex schools : findings from the NCDS' Equal Opportunities Commission.

Strand, S. (2002) 'Pupil mobility, attainment and progress during key stage 1 : a study in cautious interpretation' *British Educational Research Journal*, 28,1,63-78.

Swann, Baron, M. (1985) *Education for All : a brief guide to the main issues of the Report,* HMSO, London.

Taris, T.W. (2000) *A Primer in Longitudinal Data Analysis*, Sage, London.

Thomas, S., Sammons, P., Mortimore, P., Smees, R. (1995) 'Stability and consistency in secondary schools' effects on students' GCSE outcomes over three years' ISEIC, University of London, Institute of Education.

Thompson, B. (1998) 'Common methodology mistakes in educational research, revisited, along with a primer on both effect sizes and the bootstrap.' Invited address presented at the Annual Meeting of the American Educational Research Association, Montreal. http://acs.tamu.edu/bbt6147/aeraad99.htm (12/2005)

Tymms, P., Merrell, C., Henderson, B. (1997) 'The first year at school: a quantitative investigation of the attainment and progress of pupils' *Educational Research and Evaluation*, 3, (2), 101-118.

University of York (2004) 'Quantitative Approaches to Longitudinal Research.' Research Capacity Building Network training workshop, University of York 23/1/04

Upton, G. (1991). 'The exploratory analysis of survey data using log-linear models' *The Statistician*, 40, 169-182.

USGS (1999) 'The Insignificance of Statistical Significance Testing. What is Statistical Hypothesis Testing?'
http://www.npwrc.usgs.gov/resource/1999/statsig/stathyp.htm. (04/2004)

Van Ness, P.H. (2004) 'The Continuation-ratio Model a Tool for Exploratory Analysis of Clinical Research Data: An illustrative Analysis of Delirim in a Hospitalised Elderly Cohort' paper presented at the JSM (Joint Statistical Meetings) conference, Toronto, 2004.

Warrington, M., Younger, M. (2001) ' Single-sex classes and Equal Opportunities for girls and boys: perspectives through time from a mixed comprehensive school in England' *Oxford Review of Education*, 27, (3), 339-356.

Wedge, P., Prosser, H. (1973) *Born to Fail?* Arrow in association with the National Children's Bureau, London.

Winship, C., Mare, R.D. (1984) 'Regression Models with Ordinal Variables', *American Sociological Review*, 49, 512-525.

Woodward, W. (2002) 'GCSE gender gap continues to grow' www.educationguardian.co.uk/gcses2002. (09/2002)

Yang, M., Heath, A., Goldstein, H. (2000) 'Multilevel models for repeated binary outcomes: attitudes and vote over the electoral cycle' *Journal of Royal Statistical Society A*, 163, (1), 49-62.

Yang, M., Woodhouse, G. (2001) 'Progress from GCSE to A and AS Level : institutional and gender differences, and trends over time.' *British Education Research Journal*, 27, (3), 245-267.

Yang, M., Goldstein, H., Browne, W., Woodhouse, G. (2002) 'Multivariate multilevel analyses of examination results' *Journal of the Royal Statistical Society Series A*, 165, (1), 137-153.

Yeshanew, T., Rutt, S., Morris, M. (2005) 'Quantitative Methodology Looking at the Relationship Between School and Pupil Level Factors and Student Aspirations to Further and Higher Education' paper presented at the British Educational Research Association Annual Conference.

Additional Reading

Alba, R.D. (1987). 'Interpreting the Parameters of Log-Linear Models' *Sociological Methods and Research* 16, (1), 45-77

Aldrich, R. (1982) *An Introduction to the History of Education,* Hodder and Stoughton, London. – selected chapters

Aldrich, R., Leighton, P. (1985) *Education : time for a new act?,* Bedford Way papers no.23. Institute of Education, London.

Arnot, M. (Ed.) (1988) ' *Race & Gender. Equal Opportunities Policies in Education* ', Pergamon Press (selected chapters).

Arnot, M., Gray, J., James,M., Ruddick, J. (1998) *Recent research on Gender and Educational Performance,* HMSO, London.

Ball. S.J. (1994) *Education Reform. A critical and post-structural approach,* Open University Press.

Butler, N., Despotidou, S., Shepherd, P. 'BCS70 – The 1970 British Cohort Study. The ten year follow up' SSRU, City University, London.

Bynner, J. (1998) 'Education and family components in the transition from school to work' *International journal of Behavioural Development*, 22, 29-53

Christensen, R. (1990) *Log- linear Models* Springer – Verlag, New York.

Cox, D.R., Snell, E.J. (1989) *Analysis of binary data (2nd edition)* Chapman & Hall, London .

Crowder, M.J., Hand, D.J. (1990) *Analysis of Repeated Measures* Chapman and Hall, London.

Dearing Report (1997) 'Higher Education in the learning society' HMSO, London.

Demaris, A. (1992). *Logit Modelling,* Sage, London

DfES (1976) *The Yellow Book- Ruskin Speech* Secretary of State for Education and Science , Department for Education and Skills.

Drew, D., Fosam, B. (1994) 'Gender and ethnic differences in education and the youth labour market. A statistical review' courtesy of D.Drew

Egerton, M., Halsey, A.H. (1993) 'Trends by social class and gender in access to Higher Education in Britain' *Oxford Review of Education,* 19, (2) 183-196.

Fitzmaurice, G.M., Heath, A. F., Cox, D R. (1997) 'Detecting Overdispersion in Large scale Surveys: Application to a study of Education and social class in Britain'. *Applied Statistician,* 46, (4), 415-432

Fogelman, K.R., Goldstein, H. (1976) 'Social Factors associated with changes in Educational Attainment between 7 and 11 years of age' *Educational Studies,* 2, (2), 95-109.

Gayle, V. (1998) 'Modelling routes to Higher Education : the longitudinal analysis of ordered categorical data', *Proceedings of the Joint IASS/IAOS Conference,* Statistics for Economic and Social Development

Goldstein, H. (1991) 'Multilevel Modelling of survey data' *The Statistician,* 40, 235-244.

Goldstein, H., Rasbash, J., Yang, M., Woodhouse, G., Pan, H., Nuttall, D., Thomas, S. (1993) 'A Multilevel analysis of School Examination results' *Oxford Review of Education,* 19, (4), 425-433.

Goodman, L.A (1979). 'Simple Models for the Analysis of Association in Cross-Classifications having Ordered Categories' *Journal of the American Statistical Association* 74, 537-553.

Goodman, A., Butler, N. 'BCS70 – The 1970 British Cohort Study. The sixteen year follow up' SSRU, City University, London

Gray, J. (1981) 'Are Examination results a suitable measure of School Performance? From Publishing School Examination results : A discussion.' Institute of Education, Bedford Way papers 5, London.

Haberman, S.J. (1974). 'Log-Linear Models For Frequency Tables with Ordered Classifications' *Biometrics* 30, 589-600.

Halsey, A.H., (1993) ' Trends by social class and gender in access to Higher Education in Britain' *Oxford Review of Education*, 19, (2), 183-196.

Halsey, A.H. (1995) *Change in British Society. From 1900 to the present day 4th edition,* (chapter 6 Mobility and Education), Oxford University Press

Hart, S. (1976) 'Does the size of a family affect a child's education?' *Where,* 113, 48-50.

Hosmer, D.W., Lemeshow, S. (1989) *Applied Logistic Regression*, Wiley, New York.

Knoke. D., Burke, P.J. (1980) 'Log linear Models' Sage, London.

Landis, J.R., Koch, G.G. (1979) 'The analysis of categorical data in Longitudinal Studies of Behaviourial Development' In **Nesselroade, J.R., Baltes, P.B. (Eds.)** *Longitudinal research in the study of behaviour and development*, Academic Press, New York.

Lawton, D. (Ed.) (1989) *The Education Reform Act: Choice and contro,l* Hodder & Stoughton, London.

Maclure, S. (1988) *Education Reformed : A guide to the Education Reform act 1988*, Headway: Hodder and Stoughton, London.

MacDonald, M. (1981) *Class, Gender and Education,* Open University Press, Milton Keynes.

Majoribanks, K. (1983) 'Social class, Environments and Adolescents' Aspirations' *Educational Studies* 9,3, 135-143.

McCullagh, P. (1977) 'A logistic model for paired comparisons with ordered categorical data' *Biometrika*, 64 (3), 449-453.

Metcalf, H. (1997) *Class and Higher Education : Participation of young people from lower social classes*, The Council for Industry and Higher Education, London.

Osborn, A. F., Milbank, J.E., (1985) *The effects of early education. A report from the Child Health and Education study of children born 5-11 April 1970,* Claredon Press, Oxford.

Osborn, A.F. (1987) 'Assessing the socio-economic status of families' *Socicology*, 21, 429-448.

Parry, G. (1997) 'Patterns of Participation in Higher Education in England : A statistical summary' *Higher Education Quarterly*, 51, (1), 6-28.

Richardson, K. (1977) 'Reading attainment and family size : an anomaly' *British Journal of Educational Psychology*, 47, 71-75.

Tomlinson, S. (Ed.) (1994) *Educational Reform and its consequences*, (selected chapters), Rivers Oram Press, London.

Willms, J.D., Raudenbush, S.W. (1989) 'A longitudinal Hierarchical Linear Model for estimating School Effects and their stability' *Journal of Educational Measurement*, 26, (3), 209-23

Appendix 3

Overall percentage composition of respondents at each follow up

		1970	1975	1980	1986	1996
Sex	Male	51.7	51.8	51.9	50.1	45.2
	Female	48.3	48.2	48.1	49.9	54.8
Ethnic Group	European U.K	*	92.4	88.0	77.3	96.5
	Other European	*	1.0	0.5	0.2	0.5
	West Indian	*	1.2	1.1	0.6	0.8
	Indian/ Pakistani	*	1.5	2.1	1.7	1.7
	Other Asian	*	0.2	0.1	0.1	-
	African	*	<0.01	-	-	-
	Other	*	0.3	0.4	0.7	-
	Not stated /known	*	3.3	7.8	19.2	-
Social Class	I	4.8	6.4	5.2	4.4	7.6
	II	11.1	18.3	19.6	16.3	26.7
	III NM	11.2	8.1	7.5	5.6	10.7
	III M	43.9	43.6	36.4	22.1	40.7
	IV	14.4	12.3	10.2	5.1	11.1
	V	6.4	4.6	3.3	1.3	2.8
	Other	2.9	0.1	1.8	3.1	0.5
	Not stated/known	5.4	6.5	16.0	42.0	-
Region	North	6.1	6.1	5.6	6.2	6.1
	York & Humberside	9.0	9.7	8.6	9.8	10.3
	North West	13.1	13.1	10.8	12.0	11.5
	East Midlands	6.2	6.7	6.1	7.7	7.0
	West Midlands	10.6	10.8	9.2	10.1	10.2
	East Anglia	3.2	3.8	2.7	4.3	5.0
	South East	30.4	27.3	22.5	25.4	26.0
	South West	6.3	7.4	6.4	8.1	8.5
	Wales	5.3	5.7	4.6	6.2	5.8
	Scotland	9.7	8.9	8.8	9.7	9.6
	Overseas	0.1	0.5	0.3	0.6	-
	Not known/missing	0	0.0	14.3	0.4	-
Total		16163	13135	14875	11615	8366

Appendix 3

Overall composition of respondents at each follow up

		1970	1975	1980	1986	1996
Sex	Male	8357	6808	7713	5815	*3782*
	Female	7804	6327	7162	5800	*4584*
	Not known	2	0	0	0	0
Ethnic Group	European U.K	*	12140	13095	8983	*7603*
	Other European	*	128	80	23	*43*
	West Indian	*	152	164	74	*64*
	Indian/ Pakistani	*	197	311	202	*136*
	Other Asian	*	27	10	15	
	African	*	6	-	-	
	Other	*	40	53	85	*34*
	Not stated /known	*	445	1162	2230	*485*
Social Class	I	780	843	767	511	*586*
	II	1799	2405	2922	1888	*2056*
	III NM	1809	1069	1123	653	*825*
	III M	7123	5726	5419	2567	*3137*
	IV	2310	1620	1513	594	*858*
	V	1007	605	489	153	*217*
	Other	476	17	267	369	*35*
	Not stated/known	859	860	1536	4880	
Region	North	992	799	833	723	*291*
	York & Humberside	1449	1280	1279	1135	*488*
	North West	2116	1722	1610	1398	*548*
	East Midlands	1005	885	904	889	*330*
	West Midlands	1706	1419	1374	1173	*485*
	East Anglia	522	495	399	505	*237*
	South East	4913	3582	3349	2956	*1234*
	South West	1022	975	949	944	*404*
	Wales	859	748	691	716	*275*
	Scotland	1567	1166	1311	1125	*455*
	Overseas	12	64	43	23	-
	Not known/missing	0	0	2133	51	
Total		16163	13135	14875	11615	8366

Appendix 4

Social background variables in BCS70

Sex	*Male, Female: from raw data*
Ethnic Group	*Derived as detailed in section 3.5.1* *Collapsed to two categories white and non white for analyses.*
Social Class	*Professional/ managerial (I & II); Skilled non-manual (IIINM); Skilled manual, semi-skilled and unskilled (IIIM, IV & V).* *Social class is based on parents'occupational social class according to the Registrar General's (RG's) classification taken from the 1986 BCS70 follow up study (or earlier studies where this information was not provided). Both fathers' and mothers' social class are considered and the higher of the two is adopted as RG's social class for the family (for the main part this is based on fathers' occupational social class). For the analysis social class is collapsed to three categories.*
Parents' qualifications	*Higher Education qualification; O levels or A levels; No formal qualifications.* *Parental education is derived from responses to the 1986 and earlier follow ups. This measure is based on both parents and the highest educational qualification of either parent is used in the analysis. Parents' education is classified into three categories*
Region	*From raw data*
Tenure of accommodation.	*Council & Private rented* *Owner occupied*
Overcrowding	*> 2 persons per room*
Number of children in family	*Derived from no. of older and no. of younger siblings*
Position in family (age 5 only)	*Calculated from no. of older siblings*
Child has been in care	*1: Yes, currently or yes, in past* *0 : Never*
Neighbourhood (ages 5 & 10) / Area (age 16)	*From raw data - see table 4.19*
Attended pre-school (age 5)	*1 : LEA or private infant school; nursery; creche or playgroup* *0: no form of pre school education*
Income (ages 10 and 16)	*Based on raw data categories*
Family received benefits	*Derived from responses to' main source of income'* *1 : Benefits only ; employment & benefits; employment, benefits & investments* *0 : other*
Free School meals (age 10 only)	*From raw data - Yes or No*
School mixed or single sex (age 10 only)	*As shown in table 4.20*
School type (age 10 only)	*As shown in table 4.20*

Derivation of 'social disadvantage' variables

Rationale : Although RG's social class has recognised failings in measuring SES, it is still used because it is well known and has few categories so is manageable in terms of modelling and interpretation. Further it is available at each BCS70 follow up study. However, other measures of disadvantage over and above that covered by social class are commonly used in research and make a contribution to attainment. Paterson (1991) concludes that ' SES is best measured by multiple indicators and at multiple levels'

Social background variables (other than social class) fall into two groups, income related and family related. Hence two additional measures of 'social disadvantage' are derived from the raw data available, 'low income' and 'large family' .

	Age 5	Age 10	Age 16
Large family =1 Large family =0	Overcrowding > 2 Or no. of children >4 Or position in family >4 Otherwise N =814	Overcrowding > 2 No. of children >4 N=840	Overcrowding > 2 No. of children >4 N=837
Low income = 1 Low income = 0	 Otherwise	Income < £100* pw Or received benefits Or received free school meals	Income < £150** pw Or received benefits

Large Family

At ages 5 and 10 children from large families have lower attainment scores on average. At age 16 children from large families have higher mean score on average than those from smaller families

Low income

A general definition of poverty is incomes that are less than 60% of the national average (excluding very high earners). (This definition is used in ONS documentation and on the BBC reports of poverty).

At age 10 poverty is defined for incomes < 60% of the median income which was approx £125 in 1981. This gives about 35% of population living in poverty –probably a bit too high as reports say about 20% of population live in poverty.

At age 16 poverty is defined for incomes < 60% of the median income which was approx £144 in 1986. This gives about 31% of population living in poverty –probably a bit too high as reports say about 20% of population live in poverty.

Appendix 6

1. Definition of Social Disadvantage

At each follow up an overall indicator of social disadvantage is derived from background factors, overcrowding, large family, care, low income and benefits. Not all of these measures are available at each age group but all available information was used to derive a reliable measure.

	Age 5	Age 10	Age 16
live in overcrowded accommodation i.e. more than 2 persons per room	Yes	Yes	Yes
come from a large family i.e. more than 4 children	Yes	Yes	Yes
have been in care now or at any time prior to the study	Yes	Yes	Yes
received free school meals	No	Yes	No
the family received benefits	No	Yes	Yes
the family income is less than £50 per week (age 10) £100 per week (age 16)	No	Yes	Yes
Percentage of sample	7.6	24.1	23.1

At age 5, 7.6 % of respondents were classified as socially disadvantaged.
At age 10, 24.1% of respondents were classified as socially disadvantaged.
At age 16, 23.1% of respondents were classified as socially disadvantaged.

There is a substantial amount of overlap between the social disadvantage component variables, i.e. mostly the same people have experienced some or all of the factors. Previous research suggests that approximately 20% of the population are 'socially disadvantaged' (ONS) and the proportions classified as disadvantaged at ages 10 and 16 reflect this. At age 5 a much smaller proportion were identified as socially disadvantaged, this may be due in part to poor response rates to many of the social background questions. The fact that only 7.6.% of respondents were identified as socially disadvantaged should be borne in mind when interpreting the results.

n.b. Although a variable relating to tenure of accommodation is available at each follow up it is not included in the following analyses to avoid overfitting of the model as tenure is very strongly associated with social class.

Appendix 6

2. Derivation of attainment bands at ages 5 and 10

Age 5

Test Scores	Cumulative % frequency	Attainment band
<= 31.13	33.5	Below average
> 31.13 and < 39.85	68.7	Average
> 39.85	100	Above average

Age 10

Test Scores	Cumulative % frequency	Attainment band
<= 69.41	33.5	Below average
> 69.41 and < 89.74	68.7	Average
> 89.74	100	Above average

Appendix 6

3. Model Fits for standard log linear models

MODELS

1. The saturated model
$$\ln(f_{ijklm}) = \mu + \sum \lambda^{V} + \sum \lambda^{VW} + \sum \lambda^{VWX} + \sum \lambda^{VWXY} + \sum \lambda^{VWXYZ}$$

2. All 4 way and lower order interactions and main effects
$$\ln(f_{ijklm}) = \mu + \sum \lambda^{V} + \sum \lambda^{VW} + \sum \lambda^{VWX} + \sum \lambda^{VWXY}$$

3. All 3 way and lower order interactions and main effects
$$\ln(f_{ijklm}) = \mu + \sum \lambda^{V} + \sum \lambda^{VW} + \sum \lambda^{VWX}$$

4. All 2 way and lower order interactions and main effects
$$\ln(f_{ijklm}) = \mu + \sum \lambda^{V} + \sum \lambda^{VW}$$

5. Main effects only
$$\ln(f_{ijklm}) = \mu + \sum \lambda^{V}$$

where F_{ijklm} is the frequency of the cell with
i : level of educational attainment (Att)
j: level of social class (SC)
k: level of parents' education (PE)
l : gender (G)
m: Social disadvantage (SD)

v, w, x, y, z = Att, SC, PE, G, SD

Model Fits

Model	Age 5			Age 10			Age 16		
	LR	df	sig	LR	df	sig	LR	df	sig
Saturated	.000	0	1.000	.000	0	1.000	.000	0	1.000
Four way Interactions	3.26	8	.917	4.76	8	.917	6.23	8	.622
Three way Interactions	23.29	36	.950	26.11	36	.950	26.87	36	.865
Two way Interactions	66.67	74	.715	63.32	74	.715	66.40	74	.723
Main effects	5449.04	99	.000	6017.29	99	.000	3692.52	99	.000

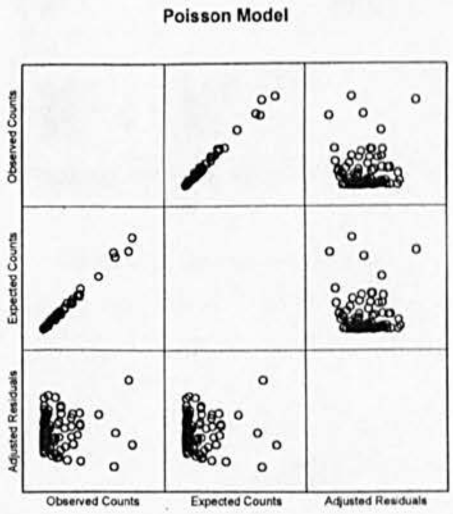
Appendix 6

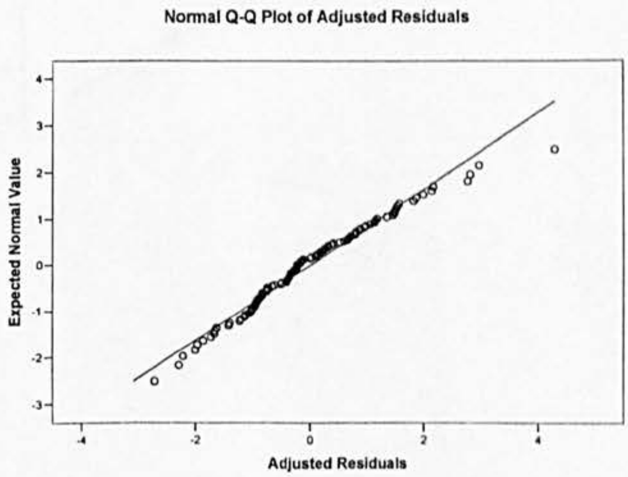
4. Residual Analysis.

Model fit is assessed by examining deviances in the log likelihood ratio statistics (L^2) between models. Examination of residuals can also help in evaluating the goodness of fit of a model.

$$L = \prod_i n_i! p_i^{r_i} (1 - p_i)^{n_i - r_i} / [r_i!(n_i - r_i)!] \qquad \text{(Everitt \& Dunn 2001)}$$

Age 5

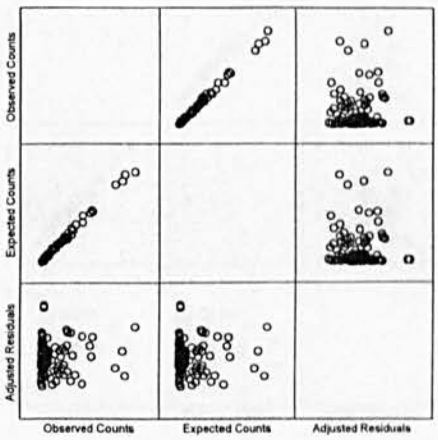




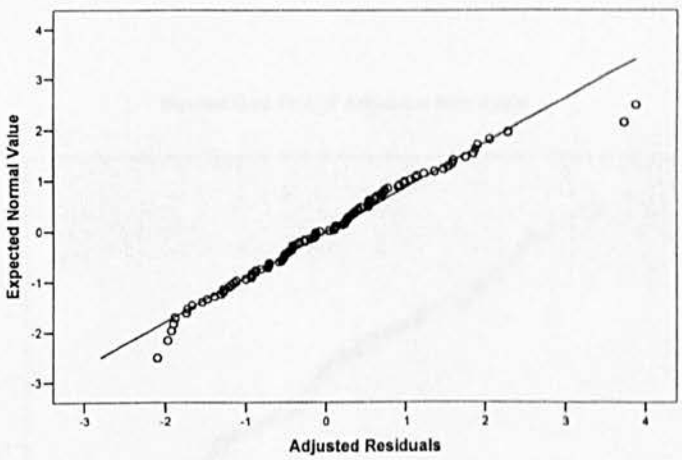
The plots show that there is a strong association between observed and expected counts.

Age 10

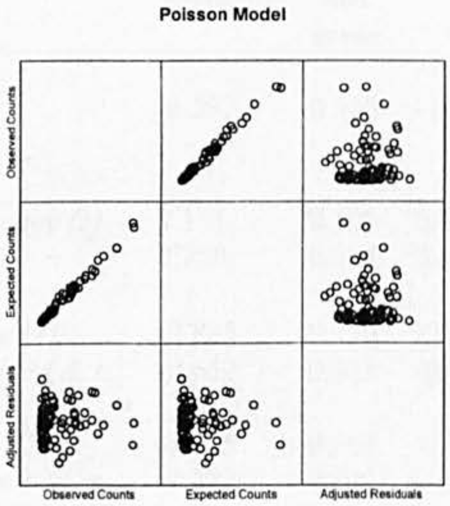
Poisson Model

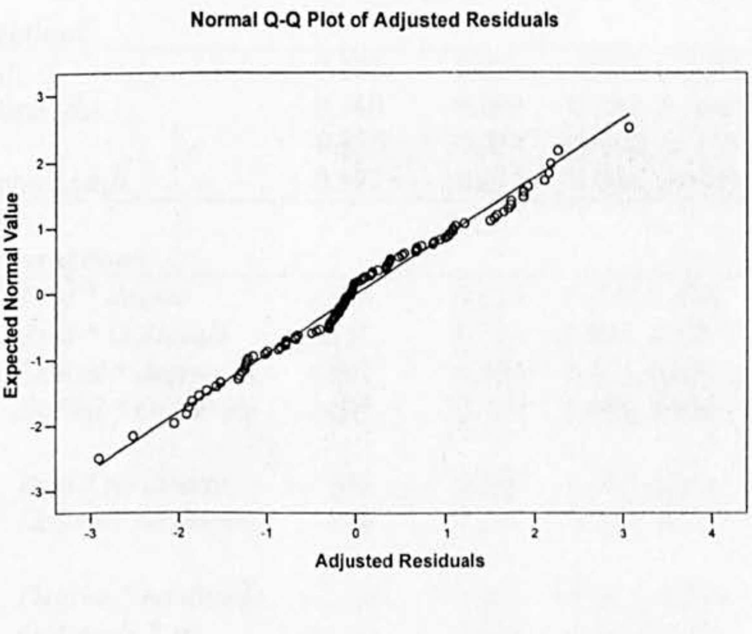


Normal Q-Q Plot of Adjusted Residuals



Age 16


Poisson Model
Observed Counts
Expected Counts
Adjusted Residuals
Observed Counts
Expected Counts
Adjusted Residuals


Normal Q-Q Plot of Adjusted Residuals
Expected Normal Value
Adjusted Residuals

Appendix 6

5. Results of ordinal log linear modelling

Age 5

Parameter		**Estimate**	**Std. error**	**95% CI**
Constant (μ)		-1.232	0.330	-1.879, -0.585
Main effects				
Attainment	*Above average (3)*	1.151	0.101	0.954, 1.349
	Average (2)	0.750	0.056	0.640, 0.860
Social Class	*Professional (I)*	-0.885	0.279	-0.337, -1.432
	Skilled (IIINM & II)	-0.652	0.303	-0.058, -1.245
Parents' Education	*Degree*	-2.015	0.363	-2.727, -1.303
	O or A levels	-1.322	0.224	-1.761, -0.883
Gender	*Female*	-0.371	0.052	-0.473, -0.270
Social Disadvantage	*None*	2.281	0.254	1.784, 2.778
Ordinal interactions				
Social class (β_1)		0.276	0.025	0.224, 0.322*
Parents' education (β_2)		0.340	0.021	0.282, 0.366*
Gender (α_1)		-0.226	0.024	-0.262, -0.168
Social disadvantage (α_2)		0.577	0.053	0.436, 0.643*
Non-ordinal interactions				
Social class * parents' Education	*Prof * degree*	6.824	0.313	6.210, 7.438
	*Prof * O/Alevels*	4.117	0.134	3.855, 4.379
	*Skilled * degree*	4.047	0.309	3.442, 4.651
	*Skilled * O/Alevels*	2.691	0.120	2.456, 2.926
Social class * disadvantage	*Prof * no disadv.*	0.577	0.288	1.141, 0.013
	*Skilled * no disadv.*	0.168	0.279	-0.380, 0.715
Parents' education * disadvantage	*Degree * no disadv.*	-0.440	0.191	-0.815,-0.065
	*O/Alevels * no disadv.*	0.156	0.194	-0.225, 0.537

*significant parameter at α=0.05

10604 cases.

baseline : below average attainment, male, semi & unskilled social class, parents with no qualifications, some social disadvantage.

Age 10

Parameter		**Estimate**	**Std. error**	**95% CI**
Constant		-3.954	0.315	-4.570, -3.337
Main effects				
Attainment	*Above average*	2.256	0.109	2.043, 2.469
	Average	1.329	0.062	1.209, 1.450
Social Class	*Professional (I)*	-1.416	0.194	-1.037, -1.796
	Skilled (IIINM & II)	-0.383	0.253	-0.112, 0.879
Parents' Education	*Degree*	-0.250	0.187	-0.616, 0.115
	O or A levels	-0.076	0.312	-0.687, 0.536
Gender	*Female*	0.010	0.052	-0.092, 0.111
Social Disadvantage	*Yes*	1.541	0.177	1.195, 1.887
Ordinal interactions				
Social class (β_1)		0.414	0.027	0.338, 0.446*
Parents' education (β_2)		0.472	0.024	0.399, 0.492*
Gender (α_1)		-0.041	0.024	-0.066, 0.029
Social disadvantage (α_2)		0.349	0.031	0.394, 0.272*
Non-ordinal interactions				
Social class * Parents' Education	*Prof * degree*	6.935	0.290	6.366, 7.503
	*Prof * O/Alevels*	4.602	0.180	4.250, 4.954
	*Skilled * degree*	3.596	0.267	3.072, 4.119
	*Skilled * O/Alevels*	2.617	0.139	2.345, 2.889
Social class * disadvantage	*Prof * no disadv.*	0.304	0.193	0.682, 0.073
	*Skilled * no disadv.*	0.010	0.187	0.357, 0.376
Parents' education * disadvantage	*Degree * no disadv.*	1.011	0.133	1.273, 0.750
	*O/Alevels * no disadv.*	0.568	0.133	0.307, 0.829

*significant parameter at α=0.05 i.e. (*standardised parameter estimates* >= |*2*|)

10569 cases.

baseline : below average attainment, male, semi & unskilled social class, parents with no qualifications, some social disadvantage.

Age 16

Parameter		**Estimate**	**Std. error**	**95% CI**
Constant (μ)		-3.070	0.333	-3.723, -2.418
Main effects				
Attainment	*Above average (3)*	4.178	0.180	3.825, 4.530
	Average (2)	2.057	0.100	1.860, 2.253
Social Class	*Professional (I)*	-3.122	0.314	-3.736, -2.507
	Skilled (IIINM & II)	-0.555	0.105	-0.760, -0.350
Parents' Education	*Degree*	-0.634	0.153	-0.934, -0.334
	O or A levels	-0.199	0.093	-0.018, -0.381
Gender	*Female*	-0.279	0.063	-0.403, -0.155
Social Disadvantage	*Yes*	1.532	0.110	1.315, 1.748
Ordinal interactions				
Social class (β_1)		0.384	0.032	0.321, 0.446
Parents' education (β_2)		0.506	0.026	0.455, 0.556
Gender (α_1)		0.081	0.030	0.140, 0.022
Social disadvantage (α_2)		0.154	0.044	0.072, 0.236
Non-ordinal interactions				
Social class * parents' Education	*Prof * degree*	5.078	0.270	4.548, 5.608
	*Prof * O/Alevels*	1.380	0.285	0.822, 1.939
	*Skilled * degree*	2.776	0.100	2.579, 2.973
	*Skilled * O/Alevels*	1.105	0.064	0.979, 1.231
Social class * disadvantage	*Prof * no disadv.*	0.223	0.154	-0.079, 0.525
	*Skilled * no disadv.*	0.187	0.078	0.035, 0.339
Parents' education * disadvantage	*Degree * no disadv.*	0.081	0.106	-0.127, 0.288
	*O/Alevels * no disadv.*	0.308	0.078	0.155, 0.461

*significant parameter at α=0.05

6363 cases.

baseline : below average attainment, male, semi & unskilled social class, parents with no qualifications, some social disadvantage.

Appendix 7

Full results of continuation ratio model analysis using SABRE 3.1

```
                         Welcome to SABRE (version 3.1)

<S> input d:/rosie/phd/sabre/finalprg.txt
    C This program reads data into the sabre program from
    C chaptsev.dat (original data chaptsev.sav)


    C NB. the outcome variable is highqual

    C 1 = no qualifications or <5 O level passes
    C 2 = >= 5 O level passes
    C 3 = A level or HE dip
    C 4 = degree or PG


    C All expl vars are in reverse order &
    C i.e. lowest through to highest

    data key sex eth soc par highqual disad
    yvar highqual
    ord 4 paratt

    read d:\rosie\phd\sabre\chaptsev.dat

       7222 observations in dataset
      13706 observations in expanded dataset

    disp v

    Name       Levels    Type
    ------------------------
    int           1      X
    key           1      CASE
    sex           1      X
    eth           1      X
    soc           1      X
    par           1      X
    qualtw        1      X
    highqu        1      YVAR
    disad         1      X
    paratt        1      X

    c
    c set up all variables as factors
    c

    factor paratt cutpt
    factor sex fsex
    factor eth feth
    factor soc fsoc
    factor par fpar
    factor disad fsd
```

C fit the ordinal logistic model and display model

```
lfit cutpt feth fsex fsoc fpar fsd
```

Iteration	Deviance	Reduction
1	19000.551	
2	16784.869	2216.
3	16740.630	44.24
4	16740.378	0.2520
5	16740.378	0.2020E-04

```
disp m
```

X-vars	Y-var
cutpt	highqu
feth	
fsex	
fsoc	
fpar	
fsd	

```
Model type: standard binary logistic

Number of observations    =  13706

X-vars df           =    10

Deviance            =    16740.378     on 13696 residual degrees of freedom
```

c display parameter estimates

```
disp e
```

Parameter	Estimate	S. Error
cutpt (1)	-0.14844	0.11740
cutpt (2)	-0.82781	0.12067
cutpt (3)	0.86055E-02	0.12202
feth (1)	0.00000E+00	ALIASED [I]
feth (2)	0.89358	0.11473
fsex (1)	0.00000E+00	ALIASED [I]
fsex (2)	-0.50673E-01	0.37418E-01
fsoc (1)	0.00000E+00	ALIASED [I]
fsoc (2)	-0.61486	0.41889E-01
fsoc (3)	-1.0435	0.86377E-01
fpar (1)	0.00000E+00	ALIASED [I]
fpar (2)	-0.50853	0.46089E-01
fpar (3)	-1.2336	0.61580E-01
fsd (1)	0.00000E+00	ALIASED [I]
fsd (2)	0.62265E-01	0.42843E-01

C remove non significant factors sex and soc.disad.

```
lfit - fsex fsd
```

```
Iteration          Deviance          Reduction
----------------------------------------------
    1              19000.551
    2              16788.621           2212.
    3              16744.669           43.95
    4              16744.419          0.2494
    5              16744.419          0.1987E-04


disp m
X-vars        Y-var
-------------------
cutpt         highqu
feth
fsoc
fpar

Model type: standard binary logistic

Number of observations    =  13706

X-vars df          =      8

Deviance           =  16744.419     on 13698 residual degrees of freedom
Deviance increase =    4.041   on 2 residual degrees of freedom
                                                  (not significant)

disp e

Parameter                 Estimate          S. Error
----------------------------------------------------
cutpt  ( 1)              -0.13870          0.11349
cutpt  ( 2)              -0.81819          0.11707
cutpt  ( 3)               0.17793E-01      0.11828
feth   ( 1)               0.00000E+00      ALIASED [I]
feth   ( 2)               0.88418          0.11434
fsoc   ( 1)               0.00000E+00      ALIASED [I]
fsoc   ( 2)              -0.61923          0.41790E-01
fsoc   ( 3)               -1.0522          0.86241E-01
fpar   ( 1)               0.00000E+00      ALIASED [I]
fpar   ( 2)              -0.51505          0.45916E-01
fpar   ( 3)               -1.2380          0.61509E-01


C add interactions with cut points to test for if effects &
C of exp vars are the same for each cut point.


tran int1 cutpt * feth
tran int2 cutpt * fsoc
tran int3 cutpt * fpar
```

C add interaction term int1 = cutpoint * ethnic group

```
lfit + int1

Iteration          Deviance          Reduction
_____________________________________________
    1              19000.551
    2              16787.470          2213.
    3              16743.228          44.24
    4              16742.973         0.2545
    5              16742.973         0.2030E-04

disp m

X-vars      Y-var
_______________________
cutpt       highqu
feth
fsoc
fpar
int1

Model type: standard binary logistic

Number of observations              = 13706
X-vars df              =    10
Deviance               =  16742.973    on 13696 residual degrees of freedom
Deviance decrease =        1.446    on  2 residual degrees of freedom
```

(not significant)

```
disp e

Parameter                 Estimate          S. Error
_____________________________________________________
cutpt  ( 1)              -0.17742E-01       0.15462
cutpt  ( 2)              -0.88472           0.23102
cutpt  ( 3)              -0.17129           0.22770
feth   ( 1)               0.00000E+00       ALIASED [I]
feth   ( 2)               0.76124           0.15649
fsoc   ( 1)               0.00000E+00       ALIASED [I]
fsoc   ( 2)              -0.61994           0.41797E-01
fsoc   ( 3)               -1.0531           0.86252E-01
fpar   ( 1)               0.00000E+00       ALIASED [I]
fpar   ( 2)              -0.51619           0.45927E-01
fpar   ( 3)               -1.2396           0.61531E-01
int1   ( 1)               0.00000E+00       ALIASED [I]
int1   ( 2)               0.00000E+00       ALIASED [E]
int1   ( 3)               0.00000E+00       ALIASED [E]
int1   ( 4)               0.19271           0.28097
int1   ( 5)               0.00000E+00       ALIASED [E]
int1   ( 6)               0.32024           0.27882
```

C remove non significant interaction term int1

```
lfit - int1
```

C add interaction term between cut point and social class (int2)

```
lfit + int2
```

Iteration	Deviance	Reduction
1	19000.551	
2	16742.503	2258.
3	16702.416	40.09
4	16702.086	0.3307
5	16702.086	0.8140E-04

```
disp m
```

X-vars	Y-var
cutpt	highqu
feth	
fsoc	
fpar	
int2	

Model type: standard binary logistic

Number of observations = 13706
X-vars df = 12
Deviance = 16702.086 on 13694 residual degrees of freedom
Deviance decrease = 42.333 on 4 residual degrees of freedom **(significant)**

```
disp e
```

Parameter	Estimate	S. Error	
cutpt (1)	-0.39865E-01	0.11501	
cutpt (2)	-0.92991	0.12197	
cutpt (3)	-0.10985	0.12613	
feth (1)	0.00000E+00	ALIASED [I]	
feth (2)	0.86431	0.11463	
fsoc (1)	0.00000E+00	ALIASED [I]	
fsoc (2)	-0.78389	0.54614E-01	
fsoc (3)	-1.5146	0.13455	
fpar (1)	0.00000E+00	ALIASED [I]	
fpar (2)	-0.50790	0.46081E-01	
fpar (3)	-1.2375	0.61642E-01	
int2 (1)	0.00000E+00	ALIASED [I]	
int2 (2)	0.00000E+00	ALIASED [E]	
int2 (3)	0.00000E+00	ALIASED [E]	
int2 (4)	0.00000E+00	ALIASED [E]	
int2 (5)	0.39109	0.94249E-01	**(significant)**
int2 (6)	0.90304	0.19370	**(significant)**
int2 (7)	0.00000E+00	ALIASED [E]	
int2 (8)	0.37034	0.10248	**(significant)**
int2 (9)	0.79052	0.18649	**(significant)**

C add interaction term between cut point and parents' education (int3)

```
lfit + int3

Iteration         Deviance          Reduction
------------------------------------------------
     1            19000.551
     2            16730.831          2270.
     3            16689.163          41.67
     4            16689.044         0.1198
     5            16689.044         0.1088E-03

disp m


Model type: standard binary logistic
Number of observations                = 13706
X-vars df          =    16
Deviance           =  16689.044     on 13690 residual degrees of freedom
Deviance decrease  =    13.042     on     4 residual degrees of freedom
```

(significant at 5%, not significant at 1%)

```
disp e
Parameter                  Estimate          S. Error
------------------------------------------------------
cutpt  ( 1)               0.22198E-01       0.11846
cutpt  ( 2)               -1.0789           0.13266
cutpt  ( 3)              -0.99692E-01       0.14349
feth   ( 1)               0.00000E+00       ALIASED [I]
feth   ( 2)               0.85738           0.11526
fsoc   ( 1)               0.00000E+00       ALIASED [I]
fsoc   ( 2)              -0.75309           0.56280E-01
fsoc   ( 3)               -1.4442           0.14055
fpar   ( 1)               0.00000E+00       ALIASED [I]
fpar   ( 2)              -0.59610           0.58927E-01
fpar   ( 3)               -1.3738           0.85692E-01
int2   ( 1)               0.00000E+00       ALIASED [I]
int2   ( 2)               0.00000E+00       ALIASED [E]
int2   ( 3)               0.00000E+00       ALIASED [E]
int2   ( 4)               0.00000E+00       ALIASED [E]
int2   ( 5)               0.32230           0.10052
int2   ( 6)               0.80836           0.21690
int2   ( 7)               0.00000E+00       ALIASED [E]
int2   ( 8)               0.30001           0.10964
int2   ( 9)               0.61354           0.20822
int3   ( 1)               0.00000E+00       ALIASED [I]
int3   ( 2)               0.00000E+00       ALIASED [E]
int3   ( 3)               0.00000E+00       ALIASED [E]
int3   ( 4)               0.00000E+00       ALIASED [E]
int3   ( 5)               0.34503           0.11061     (significant)
int3   ( 6)               0.30027           0.16187     (not significant)
int3   ( 7)               0.00000E+00       ALIASED [E]
int3   ( 8)               0.55813E-01       0.13274     (not significant)
int3   ( 9)               0.25963           0.16041     (not significant)
<S>
```

N.B. subsequently int3 is removed from model as most interactions are not significant. The actual size of the interaction term int3(5) makes negligible difference to interpretation of effect of parent's education. Assume effect is same across all transitions.