The London School of Economics and Political Science

The Dynamics of Child Poverty in Britain: Trends, Transitions and Trajectories

An Analysis of the BHPS (1991-2002)

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A thesis submitted to the Department of Statistics of the London School of Economics and Political Science for the degree of Doctor of Philosophy.

Declaration

I certify that the thesis I have presented for examination for the MPhil/PhD degree of the London School of Economics and Political Science is solely my own work other than where I have clearly indicated that it is the work of others (in which case the extent of any work carried out jointly by me and any other person is clearly identified in it).

I warrant that this authorization does not, to the best of my belief, infringe the rights of any third party.

In memory of my daughter, Noor,

and

for my mother and father

Abstract

The context for the thesis is the Government's ambitious target to eradicate child poverty by 2020 with interim targets to reduce it by a quarter by 2004/05 and to halve it by 2010/11 compared with its level in 1998/99. This remarkable pledge, with its implication of long-term commitment, is based on static headcount indicators, which measure the proportion of poor children in the population in a given year. These take no account of whether the same children experience poverty over a number of years or escape this condition. Furthermore, this pledge has not been matched by a sustained interrogation into the longitudinal nature of child poverty, which considers time in the mediation of poverty. While research on cross-sectional trends in child poverty and the associated risk factors is well established, there has been a dearth of research into the dynamic aspects of child poverty. Investigating the dynamic aspects of poverty is important since the longer the time a child spends in poverty, the more serious are the consequences to the quality of childhood, future outcomes across the life-course, and to society as a whole. The primary objective of this thesis is to explore the heterogeneity of child poverty experiences using twelve annual waves of the British Household Panel Study (1991-2002). Poverty is explored across three distinct time dimensions, namely, cross-sectional trends, short-term transitions between two consecutive years, and longer-term trajectories over the entire twelve year period. Low income is used as a proxy for poverty, with poverty defined as living in a household where income is below 60 per cent of the median adjusted for household size. As the poverty line is essentially arbitrary, the sensitivity of the findings are tested at different thresholds. Children are systematically compared with the overall population in order to assess similarities, differences, and progress over time.

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Acronyms

APE	Average partial effect
ASD	Aggregate state dependence
BCS	British Cohort Study
BHPS	British Household Panel Survey
BIC	Bayesian Information Criterion
C	Analysis sample using children
Cdf	Cumulative distribution function
CPAG	Child Poverty Action Group
DPP	Dynamic pooled probit model
DRE	Dynamic random effects model
DWP	Department for Work and Pensions
ECHP	European Community Household Panel
FACS	Families and Children Study
FGT	Foster-Greer-Thorbecke class of poverty indices
GMM	Growth mixture model
GSD	Genuine state dependence
GSOEP	German Socio-Economic Panel
HBAI	Households Below Average Income (Annual publication on poverty statistics in the UK published by the DWP.)
LCGA	Latent Class Growth Analysis
LGM	Latent Growth Model
LMR LRT	Lo-Mendell-Rubin likelihood ratio test
MAR	Missing At Random non-response
MCAR	Missing Completely At Random non-response
NCDS	National Child Development Study

OECD	Organisation for Economic Co-operation and Development
ONS	Office for National Statistics
OR	Odds ratio
PSID	Panel Study of Income Dynamics
RPI	Retail price index

Notation

Chapter 4

$i=1,2,\ldots,N$	individual i in the sample
N	total number of individuals in the sample
y_i	income of individual i
z	value of the poverty line
q	number of poor individuals
$x_i = \frac{z-y_i}{z}$	income gap ratio which measures the income shortfall for a poor person from the poverty line
P_α	Foster, Greer and Thorbecke class of poverty indices where α is a parameter which gives greater weight to income shortfalls further away from the poverty line.
P_0	headcount ratio (H)
P_1	poverty gap ratio (*PG*)
P_2	squared poverty gap *(SPG)*
j	sub-group (for example gender, employment status)
m	total number of sub-groups
$F(y)$	cumulative distribution function of income. Points along this curve show the proportion of individuals with incomes less than z.
$[z_{\min} z_{\max}]$	values of the upper and lower bounds of an interval of poverty lines
p	income quantile
ξ_p	the share of the population with income less than income quantile p
P90/P10	percentile ratio which quantifies the relative distance between two points of the income distribution. Thus, *P90/P10* compares the wealthiest and poorest 10 per cent of the population. *The P10/P50* ratio compares the poorest 10 per cent with the mid-point.

$\hat{\sigma}^2$	sample estimator of variance

Chapter 5

x_t	observed poverty status at time t
k	categories of poverty status; $k=2$ (1=poor, 2= not-poor)
$t=1,2,\ldots,12$	annual panel waves corresponding to the years 1991-2002
$p_{ij}(t)$	conditional probability of moving to state j in the current period, given that state i was occupied in the previous period.
$\delta_{x_{91}}$	observed proportion of the sample who are poor or not-poor at $t=1$
τ	observed or latent transition probabilities between consecutive time points
$s=1\ldots S$	number of Markov chains in the model
π_s	proportion of the sample in Markov chain s
$a=1,\ldots,A,\ b=1,\ldots,B,\ \ldots,\ l=1,\ldots,L$	latent variable for each time point
$\delta_{a\|s}$	probability that a respondent belongs to one of A true latent classes at t=1 conditional upon membership in Markov chain s.
$\rho_{observed\|latent}$	conditional response probabilities which give the relationship between the observed variables $(x_{91}, x_{92}, \ldots, x_{02})$ and their latent counterparts (a,$b,\ldots,l$) given chain membership.
G^2	Likelihood ratio chi-square test
f_{ij}	observed cell frequency in cell ij
F_{ij}	expected cell frequency of cell ij
N	total number of individuals in the sample
P	number of parameters
df	degrees of freedom
$Pr(Poor_{t+1} \| Poor_t)$	Probability of short-term persistent poverty
$Pr(Poor_{t+1} \| Not\text{-}poor_t)$	Probability of poverty entry

Chapter 6

$i=1,2,\ldots,N$	individual i in the sample
N	total number of individuals in the sample
y_{it}	measured poverty status, taking the value 1 if the individual is poor, and 0 otherwise
y_{it-1}	lagged dependent variable for individual i
y_{i0}	initial poverty status for individual i
γ	parameter which measures magnitude of state dependence in the dynamic random effect probit model.
$t=1,2,\ldots,12$	annual panel waves corresponding to the years 1991-2002
x_{it}'	vector of independent observable household and individual characteristics
β	vector of parameters associated with x_{it}' to be estimated
$v_{it}=\alpha_i+u_{it}$	composite error term comprised of an individual-specific time invariant effect, α_i, and a time-varying random error term, u_{it}
ρ	proportion of the total variance contributed by the individual level variance component
$\bar{x}_i=\frac{1}{T}\sum_{t=1}^{T}x_{it}$	temporal average of time-varying covariates for individual i
Φ	cumulative normal distribution function
$(\Pr(P_{it}=1 \mid P_{it-1}=1))$	probability of being poor in the current year given poverty in the in the previous year
$(\Pr(P_{it}=1 \mid P_{it-1}=0))$	probability of being poor in the current year given non-poverty in the previous year

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y_{itk}	individual i's score on poverty status, y, at time point t within latent class k t =1,2,...,12 annual panel waves corresponding to the years 1991-2002
c_i =(c_{i1}, c_{i2},...,c_{ik})	categorical latent variable, c, with k classes. c_{ik} equals 1 if individual i belongs to class k and 0 otherwise.
λ_t	value of time at t
η_{Ii}	intercept of the growth trajectory for i
η_{Si}	slope of the growth trajectory for i
η_{Qi}	non-linear lope of the growth trajectory for i
ε_{it}	time specific error term for i at t
μ_I	mean level of poverty across all individuals at the beginning of the growth process.
μ_S	mean of the slope factor and denotes the rate of change of the poverty trajectory averaged across all respondents.
μ_Q	mean of the curvi-linear growth factor.
σ_I^2	variance of the intercept which denotes the inter-individual variance in initial levels of poverty.
σ_S^2	variance of the slope, which represents inter-individual variability in the rate of change in the probability of poverty over time.
σ_Q^2	variance in the curvi-linear growth factor and shows variability in the rate at which the probability of poverty moves up or down over time.
x	covariate
$\hat{P}(k \mid Y_i)$	posterior probability, which is individual i's estimated probability of membership in group k given observed membership in each of the t measurement periods.
π_k	proportion of individuals in group k (i.e. the size of each trajectory group)

Chapter 1 Introduction

> *"Our historic aim will be for ours to be the first generation to end child poverty, and it will take a generation. It is a 20 year mission but I believe it can be done"*

Tony Blair (Beveridge Lecture, March 18th, 1999).

Part I Aims and objectives

1.1 Introduction

Child poverty is high on the political agenda. In 1999, the Government ambitiously pledged to eradicate child poverty by 2020 with interim targets to reduce it by a quarter by 2004/5 and to halve it by 2010/11. This remarkable pledge, with its implication of long-term commitment, is based on static indicators, which measure the proportion of poor children in the population in a given year. These take no account of whether the same children experience poverty over a number of years. Furthermore, this pledge has not been matched by a sustained interrogation into the longitudinal nature of child poverty.

Despite the wealth of knowledge on the rates of child poverty at particular points in time, the concept of time in the *mediation* of poverty has, until relatively recently, been largely absent from debates on poverty measurement due to a lack of longitudinal data. Until the emergence of longitudinal data, the prevailing wisdom was that poverty was mainly a persistent problem for households with specific socio-economic characteristics. However, this perception was based on a cross-sectional or static approach to poverty measurement, which cannot distinguish:

i. whether those who are poor at one point in time are the same individuals who are poor at later time points;
ii. how the experience of poverty varies across individuals in terms of the length or reoccurrence of episodes;
iii. if the annual poverty rate decreases, whether it is because poor people are no longer poor.
iv. whether households only temporarily suffer periods of low income as a result of changes in employment, health status, family structure and other factors.

Understanding these dynamic issues necessitates a longitudinal approach, which tracks the duration of poverty over time, examines the flows into and out of poverty, and analyses the processes which result in individuals spending lengthy periods of time in poverty. Research into the dynamic aspects of child poverty is especially important since the longer the time a child spends in poverty, the more serious are the consequences to the quality of childhood, future outcomes across the life-course, and to society as a whole.

The aim of this thesis is to examine the heterogeneity of poverty experiences for poor children using a longitudinal approach. It is a quantitative study using twelve annual waves of the British Household Panel Study (1991-2002). Low income is used as a proxy for poverty, with poverty defined as living in a household where income is below 60 per cent of the median adjusted for household size. This standard is the preferred yardstick for Government reporting of poverty statistics and is commonly used in wider poverty research.

This study is timely for two reasons. Firstly, within the context of the Government's aim to abolish child poverty, the dynamic analysis may provide insights into why interim targets for poverty reduction have or have not met been met given that these are based purely on point-in-time headcount measures. Secondly, whilst it is becoming more usual to consider poverty from a longitudinal perspective due the greater availability of panel data, there is a paucity of research that considers the child as the unit of analysis. Thus, the findings from this thesis will provide richer and broader insights into the changes in child poverty.

1.2 Objectives of the thesis

This thesis has a number of specific objectives:

i. To examine the nature of poverty dynamics by successively expanding upon the definition of time. The thesis does this by considering cross-sectional trends, short-term transitions between two consecutive years, and longer-term trajectories over the entire twelve year period. The cross-sectional analysis provides an important context in which to situate the longitudinal analysis. The advantage of using different time horizons is that it provides a more structured framework for understanding the heterogeneity of poverty experiences, and contributes towards a richer and broader picture of child poverty in Britain. Figure 1.1 depicts this framework.

ii. To explore the extent to which it is possible to explain longitudinal patterns of poverty in terms of observed characteristics and highlight the inequality in the risk of poverty across such characteristics.

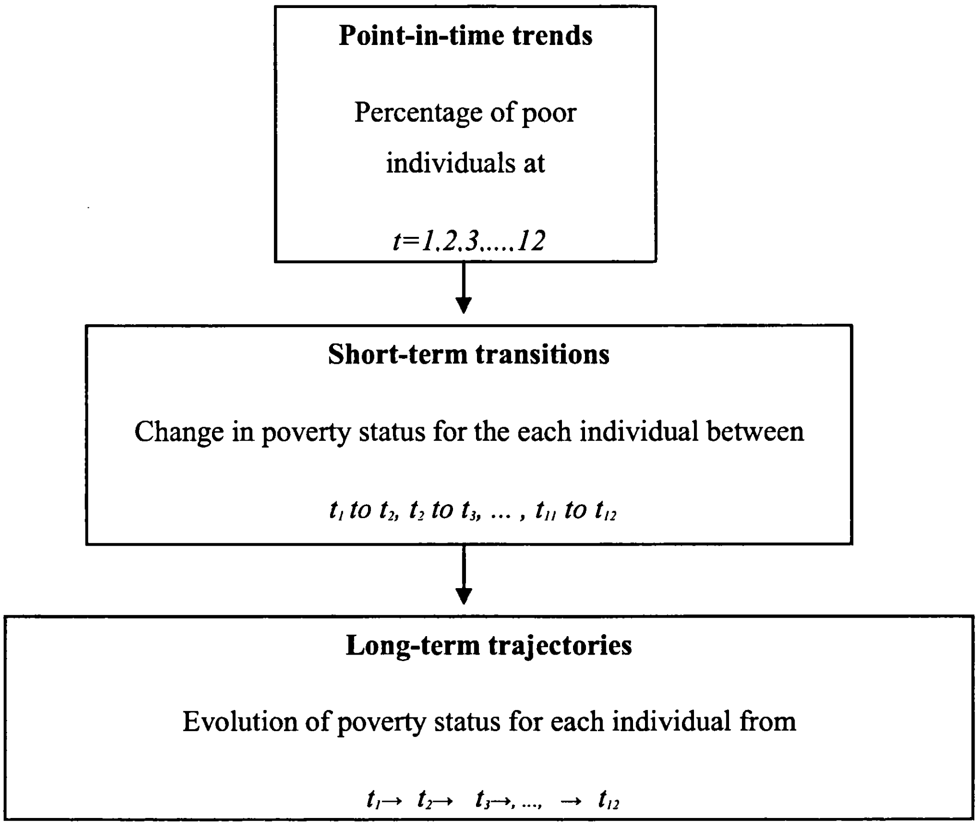
iii. To assess the importance of unobserved heterogeneity in poverty dynamics. This is considered in two ways, namely, as heterogeneity in longitudinal patterns of poverty, and as an individual risk factor for explaining poverty persistence over time.

iv. To systematically test the sensitivity of the empirical results in two important ways. Firstly, whilst the preferred income threshold for the poverty indicator is 60 per cent of the median household income, it is essentially arbitrary, hence, the analysis is also conducted at lower (50 per cent of the median income) and higher (70 per cent of the median income) bounds. Secondly, findings from the children's sample are compared with those for the whole sample. This is important as it shows how child poverty has improved or deteriorated relative to population poverty. Whilst the focus of the thesis is not on poverty for the population as a whole, the research provides an update on previous studies. A longer time frame may generate new insights into the heterogeneity of poverty experiences over time.

v. Much of the research on dynamics of child poverty in Britain is based on descriptive methods. This thesis aims to take advantage of recent developments in panel data techniques to model poverty. Some of the techniques used have not been applied to British data in general or to the study of children specifically.

The more specific aims of the thesis are highlighted in the next section, which gives a synoptic overview of each chapter.

Figure 1.1: Analytic framework for the treatment of time



Note: t is the BHPS annual panel wave (1-12) for the years 1991-2002.

1.3 Synopsis

Chapter two

Chapter two provides justifications for the topic of this thesis by exploring three specific themes. Firstly, it discusses the importance of focussing on children for the study of poverty by drawing upon literature that considers the link between poverty and systematic inequalities in various spheres across the life course, the impact of poverty upon the experience of childhood, and the consequences for wider society. Secondly, it presents evidence on whether parental incomes actually matter for children by drawing upon the cohort studies literature to demonstrate the inter-generational link between parental incomes and children's outcomes. Finally, it questions why poverty as a dynamic concept merits attention. It does this by contrasting the dynamic approach with the traditional static approach. It also describes the theoretical developments in dynamic poverty research, which provide a basis for hypothesis testing in subsequent empirical chapters.

Chapter three

Chapter three is divided into two sections. The first considers technical aspects in the definition and measurement of poverty and reviews the developments in the literature on the concept of poverty from absolute and relative perspectives. It then goes on to describe and critique two metrics for setting the poverty line, namely, income and deprivation indicators. The second part surveys the practical data requirements and compares the available data sources for the study of poverty dynamics. It goes on to introduce the key definitions used in this thesis. This includes the definition of a child, the unit of analysis, income, and poverty.

Chapter four

In order to provide a context for the longitudinal changes in child poverty, Chapter four presents analysis on the cross-sectional trends in child poverty. It considers two types of poverty comparisons, namely, cardinal and ordinal. Cardinal comparisons involve comparing numerical estimates of indices. This chapter uses the Foster, Greer and Thorbecke (FGT) class of indices. Ordinal comparisons, on the other hand, rank poverty across distributions, without quantifying the precise differences that exist between these distributions. This is done using the method of stochastic dominance. The main advantage of the former approach is the ease of comparison across distributions by comparing values of the indices, however, they are sensitive to the choice of arbitrary measurement assumptions (such as the relative weight given to different parts of the income distribution or the poverty line used) and the choice of the index itself, which may result in different estimates of poverty. Ordinal comparisons, on the other hand, do not yield a numerical value, but only rank distributions to ascertain the sign of the differences across these two distributions (but not the magnitude of poverty). As will be demonstrated, ordinal rankings are robust to a number of measurement assumptions. A profile of poverty is also constructed, which looks at the changes in poverty for children with various socio-economic characteristics. The cross-sectional estimates are also placed within the wider context of international comparisons.

Chapter five

The aggregate measures of poverty considered in Chapter four do not account for past experiences of poverty. Individuals may have spent a number of years persistently in poverty, other may just have fallen into poverty, whereas other may have escaped it. Chapter five introduces the first longitudinal empirical analysis by expanding upon the definition of time to consider short-term poverty transitions between two consecutive years. Transition rates based on observed data may lead to biased estimates if measurement error is not taken into account. This chapter employs latent Markov modelling, which allows one to separate the amount of true change in the data from spurious change which arises from measurement error. As the focus is on income poverty, it is envisaged that such error arises mainly from the inaccurate reporting of income, which leads to misclassification of those cases with incomes close to the poverty line. This chapter presents comparisons on the trajectories of observed and error-corrected transitions in order to gauge the 'true' rates of poverty mobility and persistence.

Chapter six

The aim of Chapter six is to analyse the determinants of poverty and, more specifically, the mechanisms which may underlie short-term poverty persistence. Persistence may be due to 'state dependence' (where the experience of poverty itself causes future poverty) or due to individual heterogeneity arising from observed and unobserved characteristics. It does this by estimating a dynamic random effects probit model, which controls for first-order Markov dynamics and individual heterogeneity. Two methodological issues, namely, correlated effects and initial conditions are addressed by using the Wooldridge estimator.

Chapter seven

Chapter seven expands upon the definition of time by considering the longer-term temporal nature of poverty dynamics. A key development in dynamic approaches to the study of poverty has been the classification of longitudinal poverty trajectories. Much of the research in this area has relied upon subjective categorisation rules (for example the number of and length of poverty spells) to create groups with seemingly distinct poverty patterns. Although this approach has the potential to identify similar groups as those identified by more advanced techniques, there are important methodological limitations attendant to their use, for example, the existence of heterogeneous trajectories cannot be tested but must be assumed ex ante. This chapter employs recent advances in growth curve modelling by analysing longitudinal patterns of poverty using latent class growth analysis. This classifies individuals into a limited number of groups with similar histories of exposure to poverty. Multinomial logistic regression is used to evaluate how the probability of group membership is related to various individual and household covariates.

Chapter eight

The concluding chapter presents an overview of the results and addresses some of the limitations of the thesis. It also discusses policy implications of the findings and presents suggestions for future research.

Part II Context for the thesis

1.4 Introduction

The aim of this section is to provide a context for the research presented in this thesis. Several elements are drawn together to provide a picture of contemporary child poverty in the UK. This includes a discussion of the Government's child poverty targets and how it will monitor these. The trends in child poverty and progress on meeting the goals are then presented. The key policy instruments that the Government has introduced to tackle child poverty are summarised. Wider indicators of child poverty are considered that go beyond snapshots of the proportion of children living below various income thresholds. Finally, cross-national comparisons in the trends in child poverty are presented and a discussion of the factors that explain the differences.

1.5 The Government's child poverty targets

In 1999, Tony Blair pledged that the Government will halve child poverty by 2010 and eradicate it by 2020. As a broader contribution towards meeting these targets, it has also set an interim target to reduce the number of children living in low-income households by a quarter by 2004/05 compared with its level in 1998/99 (HMT, 2004). It will monitor its progress according to three measures:

i. 'Absolute low income' indicator – the number of children living in families whose household income falls below 60 per cent of the median income in 1998/99 on a Before Housing Cost basis (BHC);
ii. 'Relative low income' indicator – the number of children living in families whose BHC household income is below 60 per cent of the contemporary median household income;
iii. 'Material deprivation and low income combined' indicator – the number of children living in households that are both 'materially deprived' and have a BHC income below 70 per cent of the contemporary median household.

The Government's interim target translates into a reduction of child poverty from the 1998/99 baseline of 4.1 million children to 3.0 million or fewer after the deduction of housing costs (AHC) in 2004/05, and from 3.1 million to 2.3 million on a before housing cost basis (BHC) (HMT, 2004). Child poverty will be judged as falling when *"all three indicators are moving in the right direction"* (DWP, 2003). In addition to these three measures, progress towards tackling child poverty will be complemented by targets for a number of multi-dimensional indicators, as tracked in the Department for Work and Pension's annual report, 'Opportunity for All' (DWP, 2005).

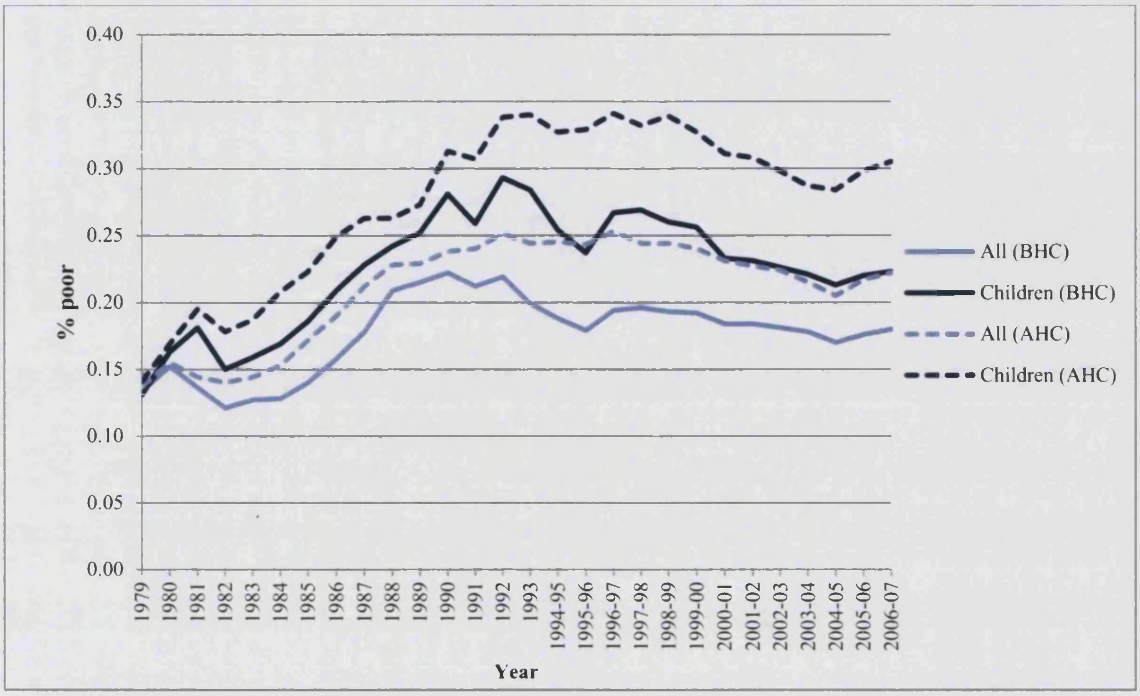
Within an international context, the UN Convention on the Rights of the Child 1989 (CRC), which was ratified by the UK Government in 1991, recognises that the particular status of children engenders specific forms of vulnerability, and it sets out the rights and entitlements needed to guarantee a child's right to survival, development and an adequate standard of living. The CRC recognizes that an adequate standard of living is essential for the child's physical, mental, spiritual, moral and social development and that child poverty has adverse effects across the life-course, including infant mortality rates, access to health and education as well as everyday quality of life of children. In particular, Article 27 enshrines the right of every child to an adequate standard of living, which is to be primarily the responsibility of the parents with the state's assistance where necessary and in accordance with 'national conditions' and means.

1.6 Long-term trends in child poverty

Official national statistics on poverty are derived from the Department for Work and Pension's annual report, *Households Below Average Income* (HBAI). It publishes a breakdown of the numbers and composition of those living below various relative and absolute thresholds of the mean and median income. Statistics are presented for both relative (contemporary) and absolute (fixed) income and on before (BHC) and after housing costs bases (AHC). The income data are derived from the *Family Resources Survey* (FRS), and before 1994/95, from the Family Expenditure Survey (FES). Up to and including 2001/02, the surveys sample households in Great Britain, and the United Kingdom from 2002/03 onwards.

Drawing upon the HBAI annual data, Figure 1.2 compares the long-term trends in child poverty with that of population poverty between 1979 and 2006/07 using a poverty line of 60 per cent of contemporary median household income. Child poverty rose steeply between 1979 and 1981, from 14 per cent to 20 per cent (AHC), and peaked twice at dramatically high levels at 34 per cent in 1993 and 1996-97. Within twenty years, child poverty had more than doubled: in 1979, 1 in 7 children lived in poverty compared with 1 in 3 in 2006/07. A number of economic and demographic factors coincided with the steep increase, for example, two recessions in the early 1980s and early 1990s and the associated rise in unemployment and economic activity; the weakening position of unskilled workers in the labour market; an increase in the share of households headed by lone parents and females; and the increased cost of state pensions due to ageing of the population (Hills, 2004). Figure 1.2 strikingly highlights that over the entire period, children faced a consistently higher risk of poverty than the overall population, and little progress has been made in narrowing this gap.

Figure 1.2: Trends in child poverty (1979-2006/07) [1]



Source: Data derived from the Institute for Fiscal Studies website http://www.ifs.org.uk/bns/bn19figs.zip (accessed in October 2008).
Notes: Poverty line is set at 60 per cent median contemporary household income.
Income data before 1994/95 are derived from the Family Expenditure Survey. Data after 1994/95 are derived from the Family Resources Survey.
The surveys sample households from Great Britain prior to 2002/03, and the United Kingdom thereafter.

1.7 Anti-poverty policies and progress on targets

The Government's strategy to eradicate child poverty can be characterised as having two elements, namely, work for those who can and security for those who cannot. This includes increasing the incomes of poor families and direct support for children through new types of policies and increased levels of child-related benefits and tax credits. Secondly, policies are targeted at reducing worklessness rates among parents and increasing job retention through the introduction of a national minimum wage and Working Tax Credit as an incentive to ensure that 'work pays'. Table 1.1 summarises some of the key policies introduced by Labour to reduce child poverty. [2]

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[1] All tables and charts in this thesis have been created in Microsoft Excel 2007 unless stated otherwise.
[2] A more detailed account of the Government's strategy to tackle child poverty over the next decade can be found in the 2008 Budget report 'Ending child poverty: everybody's business' (HMT, 2008).

Table 1.1: Summary of key policy developments targeted at child poverty

Direct support for children Increase in financial support	• Increase in Child Benefit • Child Tax Credit supplements the income of families with children, whether or not the adults in the household are working. • Reform of Child Support
Targeted programmes	• Sure Start: area-based programs in disadvantaged areas to support families with young children. The aim is to enhance physical, intellectual, and social development of babies and young children through early education and support services for parents. • Early years education: free entitlement for 3 and 4 year olds. • Educational Maintenance Allowances: cash grants for young people over 16 to encourage them to remain in school. • Child Trust Fund: tax-exempt, investment and savings account for children born from September 2002. The Government gives a 250 pound voucher for every child, with the aim of reducing the 'asset gap'.
Parental employment Making work pay	• Introduction of National Minimum Wage • Working Tax Credit: means-tested supplement to low wages. This has several elements, e.g., disabled worker element, a child care element, and couple or lone parent element. • Lower starting rates of tax and national insurance contributions
Actively supporting entry into the workforce and job retention	• National Childcare Strategy: funding for early years and childcare services. Every 3 and 4 year old is entitled to at least 12.5 hours free early education each week for 38 weeks a year. • Extended maternity and paternity leave, and improved maternity allowance. • New Deal : provides people on benefits a personal advisor to help and support them to look for work, access training, prepare for work, and inform them of further benefits. There are targeted programmes for lone parents and the disabled.

Source: Derived from HMT (2004)

Was the interim Government target to reduce child poverty by a quarter by 2004/05 from the 1998/99 level achieved? Two particular simulation studies, which forecasted the impact of new tax and benefits to reduce child poverty optimistically concluded that the Government would meet its target in reducing child poverty by a quarter by 2004/05 (Brewer, 2004; Sutherland, Sefton and Piachaud, 2003). However, the government actually missed the target by approximately 100,000 children BHC and about 300,000 children short AHC. This equates to a reduction of 21.3 per cent BHC and 17.2 per cent AHC since 1998/99, both below the 25 per cent target. Since this period, there have been two consecutive increases in child poverty[3]. Child poverty fell by 16.0 per cent BHC and 12.0 per cent AHC respectively between 1998/99 and 2006/07, thus, the original target had still not been met. A number of factors account for why the predicted fall in child poverty was overstated (Brewer et al., 2006):

i. The relative poverty threshold has been moving upwards due to real growth in average incomes, thus, the Government had been chasing a moving target.
ii. Assumptions about the take-up of child tax credits may have been too optimistic.
iii. The Family Resource Survey (which is used to estimate child poverty) under-recorded the receipt of tax credits at a time when tax credits had become a major policy instrument for reducing child poverty. Thus, HBAI may have overestimated the true extent of child poverty.
iv. Tax and benefit models analyse the *theoretical* effects of reforms without accounting for changes in the demographic structure of the population, behavioural responses to policy developments, and non take-up of benefits.

Despite missing the interim target, progress has been made by the Labour government since it came into power as evidenced by the sustained decline until 2004/05. Furthermore, by 2006/07, there were 500,000 (BHC) (and 300,000 (AHC)) less poor children compared with a decade earlier.

The Institute for Fiscal Studies analysed the drivers behind the fall in child poverty by decomposing the overall change in child poverty between 1998/99 and 2004/05 into 'incidence' effects (how the *risk* of child poverty has changed for a particular family type) and 'compositional' effects (whether the *proportion* of children in a particular family type has risen or fallen) (Brewer at al., 2006). If a group with a high poverty risk increases its population share, this is likely to raise overall poverty.

[3] The Institute for Fiscal Studies calculated that the overall increase in child poverty between 2004-05 and 2006-07 was statistically significant on the AHC basis but not on the BHC basis (Brewer et al., 2008).

The findings are summarised in Table 1.2. The two most important compositional effects that acted to reduce child poverty arose from a reduction in the proportion of children in lone-parent and couple workless families, both of which had the highest risks of poverty. However, the incidence effects for these two groups (which jointly account for approximately 30 per cent of the total reduction) outweigh the compositional effects (approximately 20 per cent of the total reduction). This suggests that a fall in child poverty amongst the workless did not arise because of a large shift into work but because of a reduced risk of poverty. This can be explained by the fact that the introduction of tax credits and out-of-work benefits have significantly increased incomes, and whilst workless households still have a much higher than average risk of poverty, 200,000 children were lifted above the poverty line in 2004/05 compared with 1997. The compositional changes that influenced increases in child poverty were for lone part-time, couple 1 part-time & 1 full-time and couple 1 not working & 1 full-time. Whilst the first group experienced an increase in population share, the compositional effect acted to increase child poverty as this group has a greater than average risk of child poverty. However, part-time work amongst lone parent was an important protective factor against the risk of risk of poverty. In 1997, almost half of all children from this family type were poor compared with 1 in 3 by 2004/05.

Table 1.2: Decomposition of change in child poverty (AHC), 1998/99 – 2004/05

Children in family type:	% of child population		Poverty rate (%)		Compositional effect	Incidence effect	Total change in poverty
	1998/99	2004/2005	1998/99	2004/2005			
Lone workless	14	13	79	72	-60,000	-107,000	-167,000
Lone part-time	5	7	45	27	15000	-132,000	-117,000
Couple workless	7	6	82	72	-63,000	-88,000	-151,000
Couple 1 part-time & 1 full-time	25	24	7	7	35,000	-8,000	27,000
Couple 1 not working & 1 full-time	18	18	28	21	2,000	-154,000	-152,000
All children	100	100	33	27	-95,000	-573,000	-700,000

Source: Brewer et al. (2006), Table 4.2, p.p.46
Poverty line: 60 per cent contemporary median income (after housing costs).
Negative numbers signify a reduction in the numbers of poor children.

1.8 Severe and persistent poverty

Snapshots of the proportion of children living below various thresholds of the poverty line reveal only part of the picture. Despite Labour's achievements in reducing child poverty, little is known about the extent of, and the characteristics of, children living in the deepest poverty. This could be conceptualised along two dimensions: (i) cross-sectionally in terms of the proportion of individuals whose incomes fall way below the poverty line or material circumstances lag behind those of the rest of society, and (ii) longitudinally in terms of the length of time individuals stay poor. Adelman et al. (2003) attempted to quantify the extent of severe poverty in Britain using the 1999 Poverty and Social Exclusion (PSE) Survey. Three indicators of poverty were derived, namely, child deprivation, parental deprivation and income poverty. A child was defined as severely poor if he/she experienced all three of the indicators; non-severely poor if he/she experienced one of two of the above measures; and non-poor if he/she did not experience any of the three measures. Accordingly, 8 per cent of children (approximately one million) were severely poor, 37 per cent non-severely poor, and 55 per cent were not poor. The study was repeated in 2005 due to the availability of additional data (Magadi and Middleton, 2005). It found that although non-severe poverty had notably declined, there was no such evidence for severe poverty:

> *"It appears that within the context of target-driven policies such as the reduction of child poverty by one-quarter by 2004, most improvements had been among those who were easiest to help, that is, those children who were closest to the poverty line and, therefore, arguably easiest to raise above it. Humanitarian concerns would suggest that policy had failed, since the group of children who were experiencing the most severe poverty had been left behind"* (Magadi and Middelton, 2005, p.p.115).

The official measures for monitoring the Government's progress on poverty take no account of whether poverty is experienced over a number of years by the same individuals. 'Opportunity for All', which is published annually by the Department for Work and Pensions contains a dynamic measure of poverty based on the British Household Panel Survey, namely, persistent low-income. This is defined as the proportion of children experiencing low-income for three out of four years.

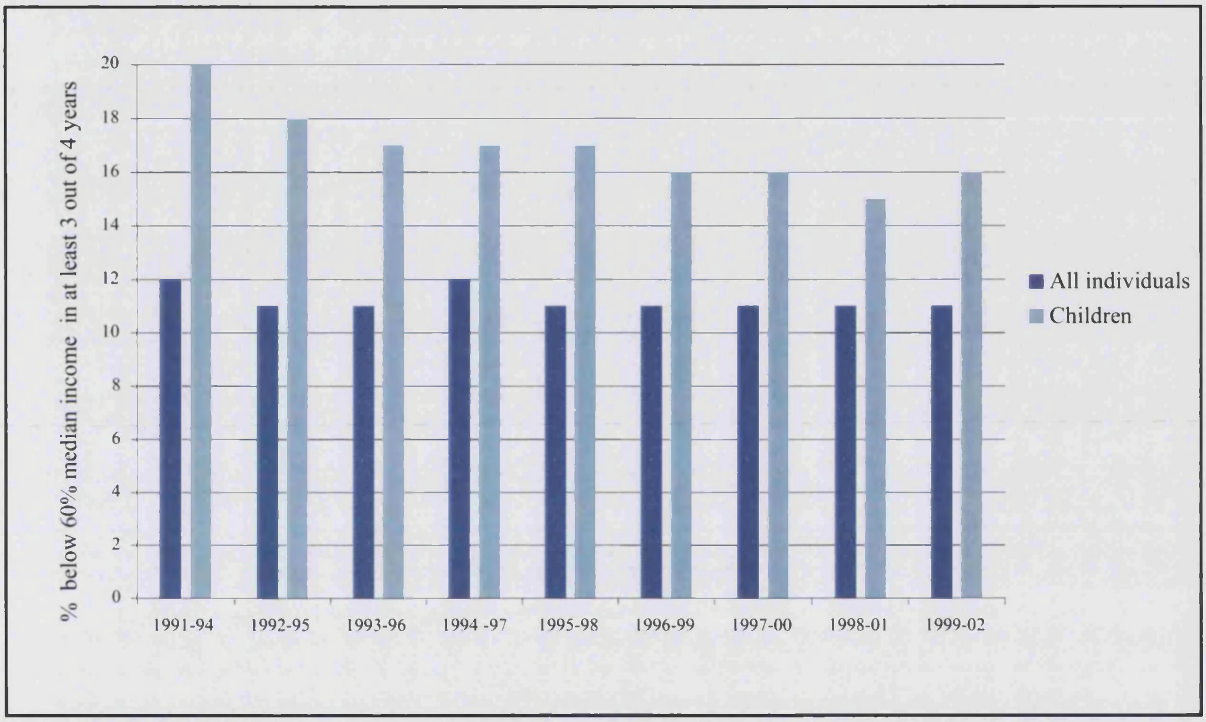
Figure 1.3 shows that children consistently experienced a higher level of persistent poverty relative to all individuals. For the 1999 to 2002 period, 16 per cent of children lived in households with income below 60 per cent of median income (BHC) for at least three years compared with 11 per cent of all individuals. Whilst there has been a significant reduction in cross-sectional child poverty since Labour came in to power, the reduction in persistent child poverty has been stagnant since 1997. In 2004, the House of Commons Work and Pensions Committee explicitly recommended that:

> "*the national strategy on child poverty develops immediate policy initiatives to assist children in severe and persistent poverty and create an explicit indicator against which progress can be measured*" (para. 89, p.p.36).

In response to the UK Government's report on its progress towards implementation of legislation, policy and practice relating to children, the Committee on the Rights of the Child acknowledged the

Government's commitment to ending child poverty by 2020 and the progress made thus far but expressed concern that *"... the Government strategy is not sufficiently targeted at those groups of children in the most severe poverty ..."* thereby acknowledging the limits of headcount driven targets (UN CRC, 2008, para 64, p.p.14).

Figure 1.3: Trends in the persistence of poverty, 1991-94 to 1999-02



Source: HBAI (2004)

1.9 International comparison of child poverty

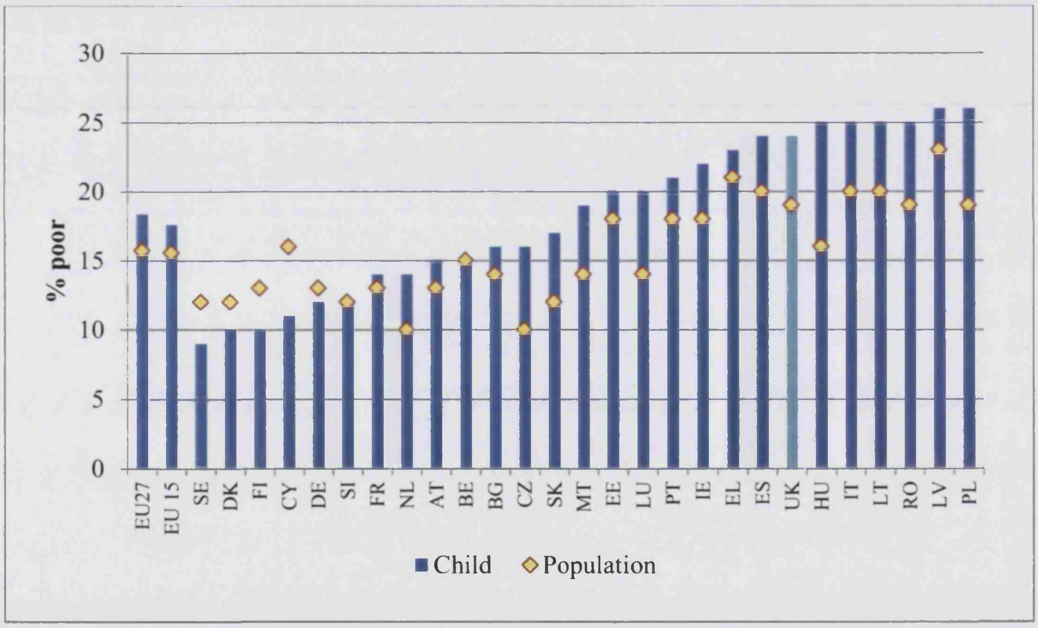
In *Measuring Child Poverty (*DWP, 2003) the Government proclaimed its goal to be 'amongst the best in Europe' in terms of relative low income. International comparisons put British child poverty into wider perspective by highlighting that the high levels experienced are neither inevitable nor typical of countries with similar average living standards. It also points to characteristics of child poverty that are particular to Britain.

Bradbury and Jänti (2001) compared the extent of child poverty by devising a league table for 25 industrialised countries. In 1995, the UK had the third highest child poverty rate (after Russia and the US) using 50 per cent of income as the poverty indicator. The authors also show that the UK was unusual compared to other countries in having an increase in child poverty over the period considered (1979-

1995). [4] A comparison across the EU15 countries shows that the UK had the highest rates of child poverty between 1995 and 2000.[5] By 2001 it had improved its ranking to 11th place out of 15 (Ritakallio and Bradshaw, 2006, Fig. 13.1, p.p. 238).

Figure 1.4 ranks the rates of child and overall poverty in 2005 among the EU27 countries. It shows that the UK is ranked joint twentieth with Spain, with a child poverty rate of 24 per cent. Hungary, Italy, Lithuania, Romania, Latvia and Poland have poverty rates that are marginally higher. There are two distinct features of the country rankings. Firstly, there is a significant gap between the UK and most of the major Northern European countries including France and Germany. That gap is again distinct from the highest performing group of Sweden, Denmark and Finland, where child poverty is almost half the rate of UK child poverty. Secondly, the risk of child poverty is lower than the rest of the population in these countries, whereas the opposite is true in the UK.

Figure 1.4: Comparison of poverty rates in Europe (60 % of median income)



Source: EU (2008) Data are for the years 2004 or 2005.

The EU's Joint Report on Social Protection and Social Inclusion (EU, 2008) identifies three key factors that underpin the UKs relatively high rates of child poverty:

[4] There are a number of shortcomings with this study as it compares national data using the most recently available for the given countries. This results in comparison of data from 1982 to 1995, which covers a period of recession and economic boom. These factors will inevitably impact upon the comparison of cross-sectional poverty rates.
[5] ECHP data using 60 per cent of the median income poverty line.

i. High level of worklessness

In 2006, the UK had the highest proportion of all children living in workless families in EU27 countries: at 17 per cent the UK rate is three percentage points higher than the next highest countries (Hungary and Belgium), twice that of France and three times that of the Netherlands.

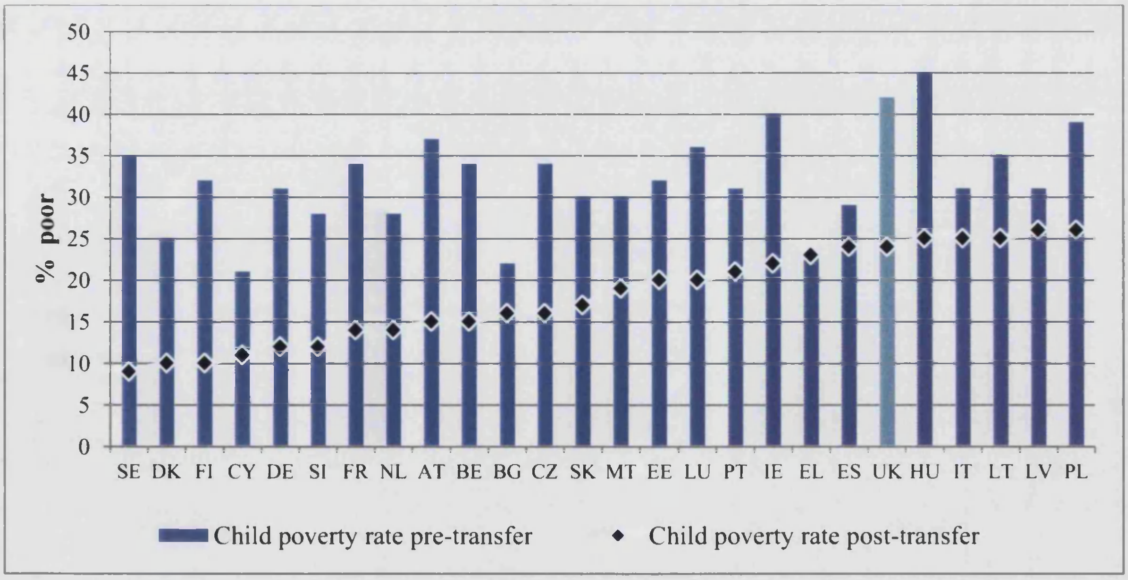
ii. High level of lone parenthood

Lone parenthood comprised 17 percent of all households with dependent children in the UK (2006). This is the second highest level in Europe after Sweden (22 percent). Worklessness in Europe mainly affects households headed by lone parents: at 67 per cent, the UK has the greatest proportion of children in workless households who belong to lone parents. This compares with the EU average of 47 per cent.

iii. Less redistributive policies

Different levels of wealth determine the level of spending on redistribution and social benefits in Europe. However, pre-transfer conditions (for example employment and earnings) and the design and effectiveness of social polices translates into countries with similar levels of wealth and social spending as a percentage of GDP experiencing widely differing levels of child poverty. Figure 1.5 shows that in 2004/2005 the UK reduced its child poverty rate by a half after social transfers (excluding pensions), however, a number of countries with relatively high pre-transfer poverty rates reduced their child poverty by a much larger proportion. Sweden, for example, which has more lone-parent families than the UK had a pre-transfer poverty rate of 35 per cent but with social transfers, reduced it by 73 percent to 9 per cent.

Figure 1.5: The impact of transfers on child poverty rates in Europe (2005)



Source: EU (2008), Table 2, p.p. 16, 60 per cent median income; income year 2004 (2005 for UK and IE).

The implication of these findings is that not only is there diversity in the levels patterns of child poverty experienced by countries at similar levels economic development, but also child poverty is not an unavoidable outcome of macro-economic conditions.

1.10 Summary

The aim of this chapter was to set out the aims and objectives of the thesis and to ground the research within a wider contextual setting. Britain is an interesting country to study the dynamics of child poverty because of explicit Government goals and policies to tackle it. Furthermore, cross-national comparisons highlight that the high levels of child poverty experienced in Britain are not typical of similar countries. The first goal to reduce child poverty by a quarter by 2004/05 was not met. An examination of poverty over different time dimensions may provide some insights into why this happened and the limitations of the Government's measures to track progress. The next chapter considers the question of why child poverty is of concern and the importance of considering poverty as a dynamic concept.

Chapter 2 Justification for the Study

"Everything you do when you're young affects you when you're older. If you're poor you're bullied, which means you won't try your best in school. You give up....If you don't do well in school you'll end up with a crap job and no money". (Young person)[6]

2.1 Introduction

Chapter 2 provides justifications for the topic of this thesis by exploring i) the importance of focussing on children for the study of poverty, ii) whether parental incomes actually matter for children's outcomes, and iii) why poverty as a dynamic concept merits attention. In Part I, Section 2.2 considers the moral and social arguments in the context of the link between poverty and systematic inequalities in various spheres across the life course, the impact of poverty upon the experience of childhood, and the consequences for wider society. Section 2.3 draws upon the cohort studies literature to demonstrate the inter-generational link between parental incomes and children's outcomes. In Part II, Section 2.4 contrasts the dynamic approach to poverty research with the traditional static approach, and Section 2.5 reviews the literature on the theoretical developments in dynamic poverty research, which provide basis for hypothesis testing in subsequent empirical chapters. The final section concludes.

Part I The theme of child poverty

2.2 The importance of studying child poverty

2.2.1 Systematic inequalities

Poverty influences children's wellbeing in complex ways and can be more detrimental to the young than to adults. For example, children are normally more dependent on the actions and decisions of others. They have no control over the conditions that they are born into, though, they influence their life chances. Poverty in childhood is a forerunner of poor outcomes in key domains such as health and education at each stage of the life course. [7] Life expectancy at birth and infant mortality rates, which are key indicators of the overall health of a nation, are both highly correlated with social class in the UK, and class in turn is correlated with income.

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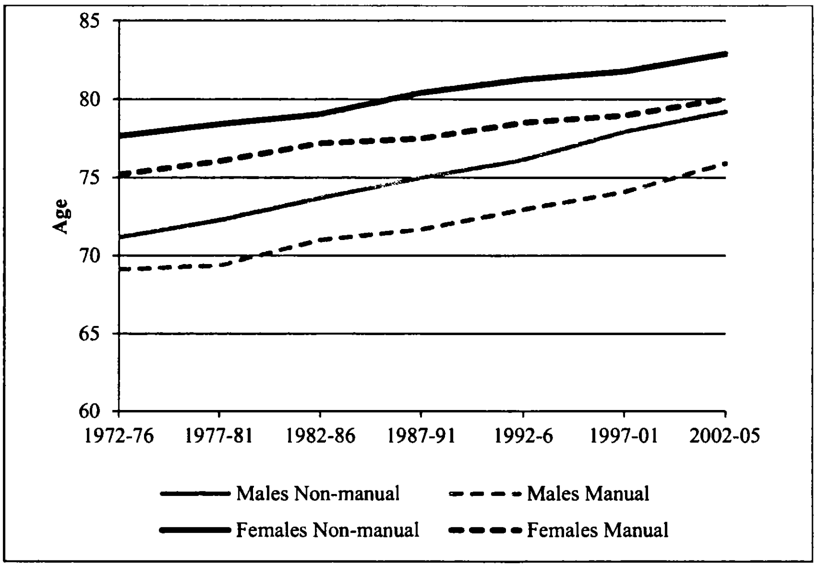
[6] Crowley, A. and Vulliamy, C. (2003), Listen Up! Children and Young People Talk: About Poverty (p.p. 15) Cardiff, Save the Children.

[7] For a detailed exposition of the persistence of social inequalities across the key stages of childhood, see Fabian Society (2006) *Narrowing the Gap, The final report of The Fabian Commission on Life Chances and Child Poverty*.

Figure 2.1 compares the life expectancy at birth for males and females from manual and non-manual backgrounds between 1972 and 2005 (ONS, 2007). Despite the general increase in life expectancy, the differential between the social classes has *widened* over the past thirty years, and is more pronounced for males than females. In 2002-05, males from non-manual backgrounds could expect to live 3.3 years longer than males from manual backgrounds. This is 1.2 years higher than in 1972-76. The social–class gradient for females was 0.4 years higher in 2002-05 compared with 1972-76.

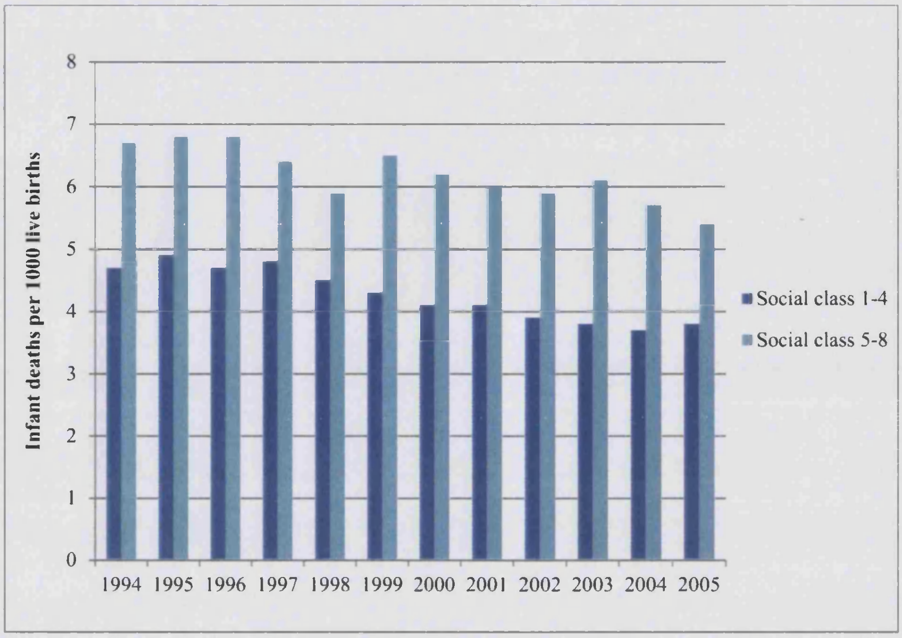
Figure 2.1: Change in life expectancy at birth by social class and gender



Source: Derived from ONS (2007) Table 1 (p.p. 5) and Table 3 (p.p.7)

In 2005, the infant mortality rate of children born into manual backgrounds was 5.4 infant deaths per 1000 live births. In contrast, the rate for children from non-manual backgrounds was 3.8 infant deaths per 1000 live births. Figure 2.2 shows that whilst infant mortality has fallen steadily for both groups, the chances of children surviving to their first birthday have remained persistently unequal over this period. Over the decade, infant deaths have, on average, been 45 per cent higher among those from manual backgrounds than among those from non-manual backgrounds.

Figure 2.2: Infant mortality rates by social class



Source: Derived from Palmer et al. (2007), p.p. 112

2.2.2 Impact of poverty upon the experience of childhood

A common reason advanced for tackling child poverty is that children represent an investment for the future (for example, national productivity and human capital). It is a key responsibility of policy-makers to ensure that the future outcomes of the current generation of children are not hindered by a lack of resources today. However, poverty also has more immediate consequences on the quality of childhood through material deprivation and limited opportunities for social participation.

'The Poverty and Social Exclusion Survey of Britain' (JRF, 2000) highlighted the extent and nature of deprivation among children in Britain. The survey compared the proportions of children lacking selected social and material necessities because their parents could not afford them, against two measures of child poverty, namely, children lacking one or more items, and two or more items. Overall, 34 per cent of children lacked one or more items, and 18 per cent lacked two or more items. A child defined as poor on either measure had a greater than average risk of being deprived than non-poor children. More specifically, although nearly all parents surveyed thought that properly fitted shoes, a warm waterproof coat, and fresh fruit or vegetables at least once a day are necessities, 1 in 50 children did not have these because they could not be afforded.

Middleton et al. (1994) have pointed out that children in poor families *"begin to experience the reality of their 'differentness' at an early age."* (p.p. 150) This has been vividly illustrated by the proliferation in child-centred qualitative work. [8] By listening to the actual voices of children experiencing poverty, more nuanced insights are gained into how low income limits their life chances. An influential study by Ridge (2002) on children's perceptions and experiences of poverty found that a *"reduced capacity to make and sustain adequate social relationships and social networks"* (p.p. 144) was clear, as well as a *"sharp awareness"* that they *"might be seen as different and find themselves isolated and marginalized"* (p.p. 144). Half of the forty subjects (aged 10-17) were not going on school trips with their peers. As a consequence, they were missing out on shared social and educational experiences. Some children were excluding themselves from school trips by not taking letters home as they felt that their parents could not afford the costs. Free school meals were also an area of concern for some children, who felt stigmatised by the method of establishing eligibility and the delivery system used by their schools.

For a child, living in poverty means being unable to enjoy the kind of childhood taken for granted in the wider society because their parents lack the necessary material resources to provide them with a decent standard of life.

2.2.3 Impact on society

The impact of child poverty extends beyond the individual to the family, neighbourhood and the rest of society (Griggs and Walker, 2008). Hirsch (2006) developed a framework for considering the "internal" costs of not tackling child poverty (the immediate impacts of poverty on childhood and future outcomes) and the associated knock-on "external" costs (short- and long-term costs to wider society). For example, poverty in childhood leads to material and social hardship, the consequences of which are effects on health and educational development. The cost to society of this includes increased social spending and burden on public services in the short-term and a loss of taxes from adults with poor job prospects linked to educational failure in childhood.

Hirsch also attempted to quantify the financial cost of child poverty to society by providing some estimates of the costs that are being incurred by the government, including:

i. £150 million a year towards the Children's Fund, which deals with the effects of poverty and social exclusion by working with children and their families to stop them falling into drug abuse, truancy, exclusion, unemployment or crime.

[8] Interested readers are referred to Redmond (2008) for a synthesis of recent qualitative studies on the experiences of children poverty.

ii. Over £500 million a year spent directly on homeless families with children;
iii. Approximately £300 million a year spent on free school dinners; and
iv. £6 million a year spent on Education Action Zones, which helps schools in disadvantaged areas.

2.3 The importance of parental incomes for children's outcomes

There is concern that the long-term effect of children growing up poor may lead to inter-generational cycles of poverty, with its underlying causes reproducing from one generation to the next. There has been a wealth of work using longitudinal data (in particular the 1958 National Child Development Study (NCDS) and 1970 British Cohort Study (BCS)) to examine childhood factors that predict adult outcomes. According to Mayer (2000, p.p. 30):

> *"Parental income is positively correlated with virtually every dimension of child well-being that social scientists measure, and this is true in every country for which we have data. The children of rich parents are healthier, better behaved, happier and better educated during their childhood and wealthier when they have grown up than are children from poor families."*

These associations, however, do not necessarily imply that poverty in childhood directly causes poor outcomes later in life as the relationship between the two are not strictly linear but are mediated by other background factors such as parental education, and individual or family unobservable factors such as genetics or ability.

Jenkins and Siedler (2007) reviewed the literature on the intergenerational transmission of poverty in industrialised countries. They conclude that:

> *"The general message is that growing up poor has a deleterious impact on later-life chances, and that this impact is not wholly explained by other factors that are themselves correlated with childhood poverty. Once one takes account of the other potential factors besides parental income (or poverty) that may play a role in the intergenerational transmission process, the association between income (or poverty) and later-life outcomes is reduced, but typically does not disappear."* (Jenkins and Siedler, 2007, p.p. 6)

A recent study using the NCDS 1958 and BCS 1970 cohort data measured the extent to which childhood poverty was related to poverty in adulthood, and how these patterns have changed over time (Blanden and Gregg, 2006). For both cohorts, children who were poor as teenagers were more likely than those who were not poor to be poor in their mid-30s. However, the risk of persistence had strengthened over time. The increased risk of poverty in young adulthood (mid-30s) for poor teenagers compared to non-poor teenagers in the 1980s was twice as large as it was for those from the 1970s.

Furthermore, after controlling for background factors, the authors found no statistically significant relationship between poverty status when respondents were teenagers in the 1970s and poverty status when they were young adults. Instead, mediating factors such as low-educated and workless parents were important factors in explaining persistence. In contrast, for those who grew up poor in the 1980s, poverty appeared to exert an independent effect on adult poverty over and above the impact of various family background characteristics.

Parental income has been shown to be strongly related to the level of their children's income when they become adults. Blanden, Gregg and Machin (2005) investigated the extent of intergenerational mobility of income. The transition matrix below (Table 2.1) shows where sons born in 1970 end up in the earnings distribution as adults, as measured by income/earnings quartiles. In a fully mobile society, 25 per cent of the children from each income group would end up in each quarter of the adult income distribution. If there is no income mobility, 100 per cent of all children would remain in the same quartile group as their parents. 40 per cent of those born in 1970 to the most affluent parents remained in the top quartile group as adults in 2000. A little over a tenth moved to the bottom quartile. In contrast, 37 per cent of those born to the least affluent parents remained in the bottom quartile at age 30 and only 16 per cent made it to the top quartile. Thus, individuals were generally more likely to end up in the income group they started in than move into another.

The authors also conducted a similar analysis for a cohort of children born in 1958 using the NCDS. They found that there was a greater level of intergenerational mobility of income than for the later cohort, indicating that the relationship between parental and children's income had strengthened over time.

Table 2.1: Income mobility of sons born in Britain in 1970

		Sons' earnings quartile aged 30 in 2000				
		Bottom	2nd	3rd	Top	Total (all sons)
Parental average income quartile[1]	Bottom	**37**	23	23	16	100
	2nd	30	**30**	24	16	100
	3rd	20	24	**29**	27	100
	Top	13	23	24	**40**	100
	Total (all parents)	100	100	100	100	

Source: Blanden, Gregg and Machin, 2005. Table 1, p.p. 4.

1. Average of incomes measured when son aged 10 and 16 using BCS 1970.

Hobcraft's (2003) analysis of the NCDS found that children growing up in poverty were more likely than other children to belong to poor households at age 23 and 33. Children living in social housing were also more likely than other children to be living in social housing themselves as adults. Furthermore, children whose fathers belonged to the lowest social groups (IV and V) were more likely to be in these social groups when they were aged 23 and 33. In addition, children who grow up in poverty are more likely to have lower self-esteem, believe that health is a matter of luck, play truant and expect to leave school at the age of 16 (Ermisch et al., 2001). Favourable as well as adverse characteristics can be passed from parents to their offspring. For example, Blanden et al. (2001), using data from the NCDS, showed those sons whose parents belong to the upper part of the earnings distribution earned 2.8 times more than sons from the lowest parental income backgrounds. Using BCS data, they found sons from the top quintile of the earnings distribution earned 3.8 times more than sons from the lowest quintile group.

Part II Poverty as a dynamic concept

> *"Cross-sectional data can be likened to a single frame extracted from a motion picture. The frame may be studied in detail but the social processes that drive the story line are lost. The danger is that conclusions derived from studying the frame misrepresent the true nature of the plot."* (Walker, 1994, p.p. 11)

The assumptions about time in the measurement of poverty are important as they affect estimates about the extent and nature of poverty. The aim of this thesis is to shed light not only on the static measures of poverty levels at different points in time, but also on the dynamics in terms of transitions into and out of poverty, the processes that lead to such transitions, and on the nature and determinants of longer-term patterns of poverty. Before proceeding to the empirical analysis, it important to clarify what is meant by the 'dynamic' approach. Leisering and Walker (1998) offer a clarification: it is both a *concept* that explores the changing nature of longitudinal poverty, and a *method* that encapsulates a variety of techniques for the statistical analysis of poverty using longitudinal data. With this in mind, the aim of this section is to explore the conceptual nature of the dynamic approach. It does this in two distinct ways. Firstly, it highlights the merits of the dynamic approach to poverty by contrasting it with the traditional static approach. Secondly, it reviews the theoretical developments associated with poverty dynamics. [9]

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[9] Methodological developments are introduced in subsequent empirical chapters.

2.4 The static versus dynamic approach to poverty

The relevance of time in the analysis of poverty was acknowledged at the beginning of the twentieth century by Rowntree (1901) who expounded a life-cycle theory of poverty. He identified that labourers and their families were not continuously poor throughout their whole lives but that cyclically changing risks of poverty entry and exit existed at specific life stages when earnings were low or household needs high. Thus, childhood and the period of bringing up children, when wages from work might not support the needs of a family, and old age when the productivity of workers declined or they were required to leave the labour market, were times of want. Young working life (before children) and later working life (after children had left home) were times of relative prosperity. Furthermore, Rowntree established that counting the number of the poor at a single point in time, as is still the practice in most countries, underestimates those affected as it conceals those who experience an episode of poverty in their lifetime:

> *"Many of these will, in course of time, pass on into a period of prosperity, this will take place as soon as the children, now dependent begin to earn. But their places below the poverty line will be taken by others who are at present living in that prosperous period previous to, or shortly after, marriage. Again, many now classed as above the poverty line were below it until the children began to earn. The proportion of the community who at one period or other of their lives suffer from poverty to the point of physical privation is therefore much greater, and the injurious effects of such a condition are much more widespread than would appear from a consideration of the number who can be shown to be below the poverty line at any given moment."* (Rowntree, 1901, p.p. 137-8)

Despite the wealth of research on the trends in poverty over different time periods, the concept of time in the mediation of poverty has, until relatively recently, been largely absent from empirical research on poverty measurement due to a lack of longitudinal data (Jenkins and Micklewright, 2007). Research originating in the USA (Bane and Ellwood, 1986) and extended to Europe by the development of new panel surveys (for example, the BHPS since 1991) and statistical techniques to analyse longitudinal poverty begun to examine the temporal nature of poverty.

In order to highlight the importance of the dynamic approach, it is useful to compare it with the traditional static approach. A static analysis of poverty provides a cross-sectional picture and can only highlight whether the number of poor people is greater or less than in previous years. In contrast, the dynamic perspective explicitly introduces time by tracking how an individual's poverty status evolves over time. As the former cannot trace individual changes in poverty status, both groups are treated as mutually exclusive entities who do not escape these states, thus, it is not possible to ascertain whether those in poverty last year remained poor or escaped this condition. A consequence of this is that static measures underestimate the number of people who experience poverty consistently over a consecutive number of years and the degree of income mobility, and thus, the volume of movements into and out poverty. The atemporal nature of static analysis leads to the assumption that the poor have homogeneous experiences of poverty. In contrast, dynamic analysis allows for *" ... a diversity of paths through poverty ... , with long or short spells in poverty, continuous or discontinuous trajectories, downward spirals and cumulative decline or escape from poverty ... "* (Leisering, 2002, p.p. 20). In other words, it exposes the *heterogeneity* of poverty experiences.

Taking the time dimension of poverty into account, Ashworth and Walker (1994) suggest that the proportion of people that experience a spell of poverty during a given period of time (prevalence) is related to four factors: (i) income stability/fluctuations, (ii) the duration of poverty spells, (iii) the extent of recurrent poverty, and (iv) 'accounting period', i.e., the length of time between income measurements (for example, monthly, quarterly, annual) and the number of measurement periods (panel waves). For example, if income volatility during a particular time period is high, poverty spells tend to be quite short and recurrent, thus, a greater proportion of people experience poverty at least once during the period (i.e., poverty prevalence is high). In contrast, prevalence will be low if incomes remain stable, thus, the same individuals remain poor. In this case, prevalence will be equivalent to the cross-sectional poverty rate as all of the poor people remain poor. With regards to the accounting period, less frequent measures may lower prevalence if individuals enter or exit poverty in the interim or because falls in income may be adjusted for by periods of affluence. The addition of new panel waves may lead to an increase in prevalence as a greater number of short-spells is revealed.

Evidence from dynamic research in a variety of industrialised countries such as Germany, the UK and the USA reveals a number of consistent findings. The proportion of people experiencing poverty over a period is considerably larger than the poverty rate suggests. Furthermore, the majority of people who enter poverty, leave this state after one or more years but there exists a small proportion who experience persistent poverty over a number of years (Bane and Ellwood, 1986; Duncan, et al.,1993; Antolin et al., 1999; Jenkins and Rigg, 2001; Layte and Whelan, 2002). A large number of individuals experience temporary poverty due to events or triggers such as changes in family structure (for example, birth of a child or divorce), health status, or job loss, however, they manage to escape after one or two years. The probability of experiencing poverty in any one year also increases the risk of future episodes, thus, those who escape tend to fall below the poverty line recurrently. Thus, poverty dynamics is characterised by a large turnover of vulnerable people in addition to a minority hard-core of the persistently poor.

Knowledge of the length of time spent in poverty has important policy implications and calls for more nuanced responses than the static responses, which mainly seek to raise the incomes of the poor above the poverty line rather than keep them out of poverty. The experience, determinants and consequences of a long episode of poverty are distinct from one-off or short recurrent episodes of poverty since the former is more likely to lead to other forms of disadvantage across the life-course. Persistent poverty points to longer-term investments such as education, job retention programmes, and improvements in asset accumulation to speed the transition out of poverty. One-off poverty, on the hand, may not have an impact on living standards if individuals can draw upon savings or other assets. A high level of recurrent poverty indicates that incomes are not remaining above the poverty line for long enough to build up material resources to stay non-poor, thus, oscillate around the poverty line. Policies are therefore required to keep individuals out of poverty rather than merely exiting it without any safety nets.

2.5 Theoretical developments

2.5.1 Theories of persistent poverty

Theories of persistent poverty have a number of different strands but the basic underlying assumption is that individual, institutional, and social consequences of poverty reinforce its persistence over time.

One explanation for persistent poverty is the alleged cultural differences of the poor resulting from behavioural inadequacies or structural barriers. The classic exposition of the 'culture of poverty' thesis is found most prominently in the work of American anthropologist Oscar Lewis (1965), who spoke of the continuity of poverty between generations, and the socialisation processes by which transmission has occurred. In his view, the lifestyles and norms of poor parents are learned by their offspring, thereby dooming them to a downward trajectory of poverty from an early age. Lewis argues that the culture of poverty,

> *"... represents an effort to cope with feelings of powerlessness and despair which develop from the realisation of the improbability of achieving success in terms of the values and goals of the larger society ... The culture of poverty, however, is not only an adaptation to a set of objective conditions of the larger society. Once it comes into existence it tends to perpetuate itself from generation to generation because of its effect on the children. By the time slum children are age*

six or seven they have usually absorbed the basic values and attitudes of their subculture and are not psychologically geared to take full advantage of changing conditions or increased opportunities which may occur in their lifetime." (Lewis, 1967, p.p. xi – xii).

Another theory of long-term poverty is the 'underclass' thesis, which has variants, namely, cultural and structural. Cultural explanations see poverty as patterns of behaviours and lifestyles that are distinct from the 'working class' and the rest of society, whereas structural explanations view poverty as the result of wider social and economic processes, which have contributed to widening inequalities in which groups with poor access to or levels of education and skills risk being left behind. The 'underclass' theory of poverty is most prominently associated with the work of right-wing American sociologist, Murray (1984, 1989, 1996). He writes:

> *"When I use the term 'underclass' I am indeed focusing on a certain type of poor person defined not by his condition, e.g. long-term unemployed, but by his deplorable behaviour in response to that condition, e.g. unwilling to take the jobs that are available to him."* (Murray, 1996, p.p.83).

Furthermore, according to Murray, other *"warning signals"* of an underclass include crime and illegitimate children.

Despite the negative connotations associated with the term, such as moral condemnation of the poor, and the vehement criticism of Murray's thesis (see, for example, IEA, 1996) , Labour MP, Frank Field, does not shy away from using the term 'underclass':

> *"... I accept that Britain does now have a group of poor people who are so distinguished from others on low income that it is appropriate to use the term 'underclass' to describe their position in the social hierarchy."* (Field, 1996, p.p. 58).

Whilst Murray focuses on behaviour as a defining feature of the underclass, Field's exposition is concerned with reducing inequalities in income and wealth by emphasising structural causes such as unemployment, widening class differences, the exclusion of the very poorest from rapidly rising living standards (Field, 1989). He points to three groups comprising the underclass, namely, pensioners, the long-term unemployed, and lone parents on welfare (Field, 1996).

This assumption of behaviour as a transmission mechanism of poverty more or less lies behind more contemporary concerns about the effect "welfare dependency" on motivation and behaviour (Murray, 1984; Bane and Ellwood, 1994). It is argued that the welfare state itself exacerbates the problems that it was designed to solve by offering social welfare provisions set at high levels relative to wages, which encourages people to choose not to work but to live on benefits. Prolonged periods of assistance lead to dependency, and welfare becomes a way of life as it undermines preference for work and self-sufficiency, particularly if claimants lose motivation, morale or skills in the process. Insofar as the welfare state induces dependency, Spicker (2002) argues that the welfare state creates a 'poverty trap' as the system requires people to be poor as a condition of receiving benefit with increases in income leading to a withdrawal of benefit. Such theories of poverty have been criticised for exaggerating the extent of long-term poverty and conceptualising the poor as an unchanging group and behaviourally separate from the rest of society. They do not take into account that spells of poverty may be one-off or repeated. Furthermore, most spells appear to be of relatively short duration and only a minority of people remain poor throughout their lives.

In the 1980s, research from the US began to empirically challenge the notion that poverty was long term and cumulative (Duncan 1984, Bane and Ellwood, 1986). It emerged that the proportion of the population experiencing poverty was much greater and more heterogeneous than that estimated by traditional headcounts of the number of persons or households below the poverty line. Furthermore, it comprised individuals who experienced it only once in their life time for a short period, multiple times for varying lengths of time, and finally continuously, either for lengthy periods or throughout their life. Whilst the hypothesis of persistent poverty held for the last group and was a possible risk for the second, it did not hold at all for the first group.

Leisering and Walker (1998) criticised the earlier research on the culture of poverty on account of being empirically unrepresentative as only marginalised groups for whom long spells of poverty were common, for example, the homeless and residents of poor neighborhoods, were sampled. Secondly, the research was methodologically limited as it was based on retrospective biographies using interviews at a given point in time to determine how the subjects became long-term poor. Thus, those who had left the area or escaped poverty were excluded. On a theoretical level, the assumption that cumulative disadvantage leads to downward spirals of deprivation treats the poor as a static group and passive victims rather than active agents who are capable of escaping poverty, i.e., the focus was on routes *into* poverty with no scope for routes *out of* poverty. Explanations of poverty which focus on the behaviour and values of those deemed to be members of the 'underclass' divert attention from wider social, economic and political causes. Poor people share the same aspirations as the rest of society but social and economic constraints prevent them from achieving them.

2.5.2 Individualisation thesis

The individualisation thesis was first propounded by Ulrich Beck (Beck, 1991) who suggested that the influence of traditional norms and regularities such as social class structure, religion and family have lost their importance as a source of individual orientation in post-industrial society. As such, individual lives no longer follow a 'prescribed' life-course, for example, a clear demarcation between the various phases of the life (childhood, education, economic activity, retirement), defined gender roles within the household (housewife, male breadwinner), strong bonds within the nuclear family, and uninterrupted full-time careers. Instead, new social and economic risks have given rise to a greater heterogeneity of possibilities, and individuals tend to arrange their own biographies according to their own choices.

The feminisation of work, for example, means that workers are increasingly combining a career with family responsibilities. This has been accompanied by a shift away from the traditional "male breadwinner" towards dual earners. Individuals are also faced with a variety of fluctuations and breaks in the life-course, many of which are mutually reinforcing and involve the risk of poverty or income uncertainty. For example, the rise of divorce and lone parenthood mainly affects women who may have to reduce their economic activity to care for their children. There has been an increasing importance of human capital, which requires longer periods of learning. This has led to a growing disparity between high-skilled and professional workers with secure and well-paid jobs in contrast to low- or unskilled workers who tend to be excluded from the labor market or depend on temporary and often low-paid jobs.

The individualisation thesis was empirically tested by Leisering and Leibfried (1999) on the basis of their study on social assistance careers in two German cities over a six year period. Taking Beck's thesis, they develop a life-course approach to poverty dynamics in which three key principles are identified, which they label 'temporalisation', 'biographisation' and 'democratisation':

> *"Poverty is no longer (if it ever was) a fixed condition or a personal group characteristic, but rather it is an experience or a stage in the life course. It is not necessarily associated with a marginal position in society but reaches well into the middle class. Poverty is specifically located in time and individual biographies, and, by implication, has come to transcend traditional social boundaries of class. These characteristics of present-day poverty can be referred to as temporalisation, biographisation and democratization (or 'transcendence') of poverty."* (Leisering and Leibfried, 1999: p.p. 239).

Leisering does not deny the existence of long-term poverty nor conceptualises contemporary poverty as unproblematic, however, he argues that poverty:

"is more complex, and is harder to grasp and to combat than it may have been at a time when easily comprehensible categories of people in need could be identified. While the finding that spells of poverty are often short is good news, the diagnosis of a democratisation of poverty paints a darker picture of society than conventional views of poverty do." (Leisering,2002: p.p. 4).

Indeed, he calls for dynamic analyses of poverty to expose the heterogeneous experiences of the poor by allowing for different temporal patterns of poverty, transitions, cumulative decline, and spells of varying lengths.

2.6 Conclusion

There are three broad reasons as to why the study of child poverty is important. Firstly, the experience of childhood itself is blighted by economic hardship. Secondly, there are clear gradients in the disparity in outcomes faced by children from different social backgrounds. This suggests that children's life prospects are determined by contingencies of social fortune – a mere accident of birth – rather than by natural ability. The evidence indicates that the likelihood of a child experiencing advantageous/disadvantageous outcomes across the life-course is strongly related to the economic position of their parents. This implies that from birth, children have unequal chances of achieving success in life. Not only do poorer children have a higher likelihood of experiencing adverse risk factors, but the experience of such risk factors is likely to have a greater effect on them throughout their lives than on more affluent children. Finally, there are also future economic costs to society because of child poverty, which are incurred in a multiplicity of ways, for example, through wasted talent, crime and anti-social behaviour, the cost in lost earnings of non-participation in education, employment or training, and the costs of future medical and social care as a result of the long-term impact of poverty on people's mental and physical health.

Static analysis sheds light on *how many* people are poor and to which social and demographic groups they belong to, whereas dynamic analysis can highlight *how, why,* and *when* incomes rise or fall below the poverty threshold. It is possible to gain a richer understanding of the heterogeneous experiences of poverty by considering transitions, sequencing, and the duration of poverty over time. Furthermore, dynamic approaches to poverty call for more nuanced policy responses than static approaches. The experience of a persistent poverty is much more of a concern than one-off episodes since the former is more likely to lead to other forms of disadvantage across the life-course. Developments in the theoretical literature posit a number of explanations about the causes of short- and long-term poverty. These explanations will be used in subsequent chapters as the basis for testing specific hypotheses on the dynamics of poverty.

Chapter 3 The Concept and Measurement of Poverty

"Few aggregate economic indicators are watched as closely as poverty statistics, and yet there is probably less professional consensus on the measurement of poverty than on any other indicator."

(Duncan (1987) quoted in Hagenaars (1991) p.p. 137)

Part I Conceptual background

3.1 Introduction

Most methods of poverty measurement require a minimum threshold of resources for distinguishing the poor from the non-poor. The literature on poverty measurement contains at least three different, but connected, debates: i) defining poverty, ii) establishing a threshold of the poverty indicator for identifying the poor, and iii) aggregating the available indicator information into a measure of poverty. At each stage, there are different views on the concept of poverty (whether it is relative or absolute) and different methods of implementing the concepts in practice (for example, whether income or indicators of deprivation should be used to identify the poor). Furthermore, the assumptions underlying each stage have important implications because they affect the extent of poverty.

Part I of this chapter reviews the developments in the literature on the concept of poverty from absolute and relative perspectives. It then goes on to describe and critique two metrics for setting the poverty line, namely, income and deprivation indicators. Part II surveys the data requirements and available survey data for the study of poverty dynamics, and introduces the key definitions used in this thesis.

3.2 The concept of poverty

3.2.1 Absolute poverty

At the close of the Victorian era, Seebohm Rowntree's pioneering study of poverty in York, which was published in 1901, is seen as one of the first attempts to not only determine the level of poverty, but also to define it. His "primary poverty line" was based on the retail cost of *"the minimum necessaries for the maintenance of merely physical efficiency."* (Rowntree, 1901, p.p. 117). This was an early definition of absolute poverty. The poverty line was based on the cost of "basic needs", which included food, rent, and necessary "sundries" such as fuel and clothing. Minimum food needs were measured on the basis of costing up a minimum "food basket" that met nutritionists' ideas of necessary calorie and protein intake, and was devised from the diets recommended for workhouse paupers in 1897. For rent, and expenditure on clothing, fuel and other sundry items, Rowntree had no readily available 'scientific' standard of minimum needs. For example, poverty lines for clothing and fuel and sundry items were ascertained by interviewing the poor and asking them what was a 'reasonable' minimum expenditure on these items. Thus, Rowntree's measure of poverty was derived from a combination of expert opinion, actual expenditure, and the costing of items based on people's perceptions of necessity. He conceptualised poverty as being absolute: bare subsistence distinguished the poor from the non-poor.

Other absolute definitions of poverty allow for more than just subsistence, however, being fixed at a particular point in time is a characteristic common to all. An example of a contemporary absolute poverty line is the World Bank's dollar-a-day yardstick. This has been the standard international measure of absolute poverty since 1990, when it was first used in the Bank's *World Development Report* (World Bank, 1990). Despite being readily understandable, the measure has been widely criticised, most notably by economist Sanjay Reddy and philosopher Thomas Pogge (Reddy and Pogge, 2002). They argued that the poverty line was chosen arbitrarily and does not correspond to a meaningful interpretation of poverty in terms of the resources that are required to fulfil elementary capabilities such as shelter and nutrition. It, thus, lacks practical significance for application to poverty alleviation policies. Secondly, to compare poverty in countries with different currencies and price levels, the World Bank uses "purchasing power parities", which reflect the average price levels for *all* commodities in the market (weighted by their share in international expenditure) rather than a small subset of commodities that are likely to be important to the poor for subsistence. Furthermore, the income/consumption data on which the global poverty statistics are based are often of poor quality or unavailable, leading to unreliable inferences and conclusions about the level and severity of global poverty. Finally, by holding a poverty line constant in real terms, a change in living standards is not allowed to affect the absolute poverty line.

3.2.2 Shifting debates: towards a relative definition of poverty

In post-war Britain, the welfare state together with rising material affluence was assumed to be abolishing the last traces of poverty and narrowing the gap between the living standards of the rich and poor. However, during the 1960s and 1970s there was a crucial shift in the understanding of poverty in academic and public debate.

Townsend (1962) criticised Rowntree's methodology on a number of grounds. He argued that the consumption patterns and needs of people will be influenced by individual habits and by customary patterns of consumption in society, thus, estimates of needs cannot be absolute but must be relative to the kind of society in which one is living. He also criticised the standards of absolute poverty for having restricted attention to the preservation of physical needs without acknowledging the impact of wider societal factors on poverty:

> *"Man is not a Robinson Crusoe living on a desert island. He is a social animal entangled in a web of relationships at work and in family and community which exert complex and changing pressures to which he must respond, as much in his consumption of goods and services as in any other aspect of his behaviour"* (p.p. 219).

According to Townsend, Rowntree's definition of poverty is arbitrary and undermines claims of absoluteness given that sundry items associated with necessities change over time and vary according to the society that one lives in. By focusing on the needs of poor people, a circularity in the definition is introduced: the needs of the poor are defined by the expenditures and perceptions of the poor, and ignores the standards of living of wider society. Rowntree's methodology was also viewed by Townsend as abstract as it was based on hypotheses of what people should do to survive on low incomes rather than what they actually do.

Townsend and Abel-Smith fist applied the relative concept of poverty in the study *The Poor and the Poorest*. They advocated more behaviourist approaches to poverty, where the actual living (and consuming) conditions and behaviour of the poor were observed by researchers in order to ascertain the level of minimum resources. The poverty line was defined as a family's position relative to social security levels (140 per cent of the level of National Assistance benefits). The findings were viewed as a "rediscovery of poverty" as it emerged that many people were not, in fact, sharing in the economic success of the country. Between 1954 and 1969, poverty had increased from 8 per cent to 14 per cent. Furthermore, the largest group in poverty was the "working poor". In subsequent work, Townsend offered, what has become, a classic definition of relative poverty:

> *"Individuals, families, and groups in the population can be said to in poverty when they lack the resources to obtain the types of diet, participate in the activities and have the living conditions and amenities which are customary, or are at least widely encouraged or approved, in the societies to which they belong. Their resources are so seriously below those commanded by the average individual or family that they are, in effect, excluded from ordinary living patterns and activities."* (Townsend, 1979, p.p. 31)

Although this definition of relative poverty is widely accepted, the idea itself dates back to the writings of Adam Smith. In his treatise on *The Wealth of Nations* (1976 [originally published in 1776]), Smith famously propounded that:

> *"By necessaries I understand not only the commodities which are indispensably necessary for the support of life, but whatever the custom of the country renders it indecent for creditable people, even of the lowest order to be without"* (p.p. 869)

He cited a number of goods, such as leather shoes and a linen shirt that would be considered as socially determined necessities of his time. He continued:

> *"Custom... has rendered leather shoes a necessity of life in England. The poorest respectable person of either sex would be ashamed to appear in public without them. In Scotland, custom has rendered them a necessity of life for the lowest order of men; but not to the same order for women ... In France they are neither a necessity for men nor for women... "* (p.p. 870)

Poverty as a relative concept has wide appeal. As modern societies, in general, become more affluent over time, all income groups tend to surpass levels of absolute poverty that were fixed in previous periods. For this reason, relative definitions of poverty are generally favoured as they takes into account rising living standards. Stakeholders in the poverty debate, such as the Child Poverty Action Group, argue that *"all approaches to definition must be relative to society, time, place and observer. Thus there can be no absolute definitions: they are all relative."* (Child Poverty Action Group, 2001, p.p. 20) Furthermore, the concept of relativity is inherent in the *Convention of the Rights of the Child* where children have a right to a standard of living adequate not only for physical development but also moral and social development: none of these can be defined without reference to the prevailing norms of a particular society.

A clarification between absolute and relative measures of poverty is offered by Sen's (1983) 'capabilities' approach. Sen argued that while goods can be purchased using incomes, the capabilities derived from the utility of such goods should be used to judge standards of living: *"poverty is an absolute notion in the space of capabilities but very often it will take a relative form in the space of commodities"* (Sen, 1983, p.p. 161). This implies that the material resources necessary to meet the same absolute capability (such as being well nourished, appearing in public without shame, visiting friends) will vary according to the cultural and historical development of a particular society. As a possible solution to the deficiencies of the World Bank's poverty line, Reddy and Pogge (2002) advocate Sen's capability approach, whereby an international poverty line is constructed on the basis of capabilities, which are selected through an international consultative process, and using the amount of money that would be required to meet such needs to make international poverty comparisons. Lister (2004) argues that poverty should not necessarily be equated as capability failure as factors other than low income can give rise to the latter.

The question of whether poverty should be viewed as an absolute or relative condition is important as it partly determines policies that might reduce poverty. Poverty as measured by an absolute line may be abolished by economic growth. Poverty as measured by a relative threshold can only be reduced by a decrease in income inequality. An overall rise in the standards of living in a society may not necessarily result in a drop in the share of the poor population if living standards increase uniformly over all strata.

The concepts of 'absolute' and 'relative' poverty lines described above only refer to how poverty lines are adjusted in different contexts. There is even less agreement on the most appropriate methods for setting the threshold of the poverty line.

3.3 A review of the metrics for setting the poverty line

3.3.1 Use of income distributions: mean or median income thresholds

The level of income largely determines access to many of the goods and services consumed in daily life, thus, is commonly used as a yardstick for setting the poverty line. Atkinson (1987) argues that poverty is a function of an individual's position in the income distribution and so one should adopt a poverty line that incorporates some notion of the distribution of income. Thresholds of this type are commonly identified using *a priori* cut-offs representing the income level below which individuals have a standard of living that falls below that of the rest of society. Such poverty lines may be absolute or relative. Absolute poverty lines do not depend on the income distribution in society but reflects a fixed level of income required for a minimum standard of living. In contrast, relative thresholds are derived directly from the income distribution and are commonly denoted by a fraction of the mean household income (average household income) or median (the midpoint when all persons or households are ranked in ascending order of household income) to distinguish the poor from the non-poor.

One argument in favour of the mean is linked to income inequality: by using the median, two countries might have the same percentage of poor whereas the percentage of people with an income between the mean and median may be very different (Townsend, 1979). Advocates of the median argue that this is a more appropriate measure as it is the lower part of the income distribution with which poverty research is concerned. Furthermore, the mean is sensitive to measurement errors at the extreme tails of the income distribution, hence, the median is a more robust measure of central tendency for establishing a poverty line (Bradbury and Jäntti, 2001).

Measures of relative low income based on fractional methods are widely used in industrialised nations. No official poverty line exists in Britain, but the government presents poverty rates in the annual HBAI series using thresholds of 50, 60 and 70 per cent of the median income. *Opportunity for All*, the government's annual audit of poverty, also includes measures where the poverty line is fixed in real terms at its 1998/99 level (DWP, 2005). Furthermore, the Statistical Program Committee of the European Union has recommended the 50, 60 and 70 per cent thresholds of equivalised contemporary median income, with preference for the 60 per cent median indicator (Eurostat, 2000). Whether the mean or median is chosen, the proportion of the population counted as poor will always be relative to the particular threshold chosen: the higher the threshold, the greater the proportion of people who fall below the poverty line.

3.3.2 Multiple indictors of deprivation

A further development in poverty measurement has been the use of deprivation indicators either in conjunction with or as an alternative to income. The DWP is developing an indictor of material deprivation as a complement to its income measures in order to monitor its progress towards the abolition of child poverty (DWP, 2003). Two theoretical arguments exist for the use of deprivation indicators. Townsend (1979) argued that poverty results from a lack of command over sufficient resources, and deprivation is a consequence of poverty. In contrast, Ringen (1985) criticised the idea that income should be the sole indicator of welfare, particularly since empirical studies showed that that a lack of material resources is neither a necessary nor a sufficient condition for poverty. Furthermore, equal material resources did not necessarily result in equal welfare, and that welfare is not necessarily a function of material resources. He went on to argue that that poverty *is* deprivation and should be measured directly as poor living conditions and consumption rather than indirectly as the lack of resources using an income measure.

Townsend built up a list of sixty indicators pertaining to social and material hardship and reduced these to twelve. A deprivation index was formed by giving each individual a score depending upon the number of items they lacked. He then related the distribution of the deprivation index with the distribution of income to determine if there was a unique level of income beneath which the risk of deprivation increased disproportionately with a fall income. This unique point represents the income level at which individuals cannot participate in the general style of living in society. Thus, Townsend defined poverty as relative deprivation caused by a lack of resources. His definition of the poverty line depends on the hypothesis that at a certain income level, deprivation increases disproportionately.

Piachaud (1981) questioned Townsend's claims to objectivity as he did not take account of taste or choice as an explanation for a lack of a particular indicator (for example, a lack of fresh meat may be a function of vegetarianism rather than low income). In addition, the derivation of an acceptable list of indicators was undemocratic as it depended on expert opinion rather than on a notion of acceptability defined by the general public. Townsend's definition of the poverty line rests on the assumption that an elbow-point is uniquely identified. Although his study identified a poverty line based on this method, one may not be defined if a decrease in deprivation is part of a smooth decreasing function of income.

The limitations of Townsend's methodology were refined in the 1980s in studies that also used the deprivation indicator approach. The *Breadline Britain* survey attempted to develop a 'consensual' measure of poverty based on the public's perceptions of necessity (Mack and Lansley, 1985). [10] The authors claimed that their study:

> "*aims to identify a minimum acceptable way of life not by reference to the views of 'experts', nor by reference to observed patterns of expenditure or observed living standards, but by reference to the views of society as a whole. This is, in essence, a consensual approach to defining minimum standards*" (p.p. 42-43).

The survey asked respondents to decide which of 35 items they deemed to be necessities to avoid hardship. Those with 50 per cent support were argued by the authors to be consensually approved necessities. Respondents were then asked whether they lacked those items and whether it was due to a lack of resources to purchase them or through choice. A poverty standard was then set such that anybody who lacked three or more necessities because they could not afford them was regarded as poor. A number of criticisms ensued from Mack and Lansley's 'consensual' approach (Veit-Wilson, 1987; Hallerod, 1994). The study was, in fact, based on the majority view rather than consensus, and there was no theoretical reason for choosing 50 per cent as a cut-off for defining necessities. In addition, criticism focused on the rejection of 'expert' opinion given that the list of potential necessities was drawn up by the researchers and not their subjects. Asking people about what they cannot afford introduces subjectivity into the measure and possibly understates the extent of hardship (Berthoud and Bryan, 2008).

The most recent attempt to define socially acceptable living standards in Britain was undertaken by the Joseph Rowntree Foundation (Bradshaw *at al.,* 2008). The aim was to derive a minimum income threshold that is "*... socially unacceptable for any individual to live below*" (p.p. 52). The list of items

[10] The methodology was more recently repeated in Gordon and Pantazis (1997) and Gordon et al., (2000).

that defined minimum income standards were based on public consensus and expert opinion and included not only basic needs such as food, fuel, clothing, and shelter but also allowances necessary for social, recreational, and cultural participation in society. Thresholds were derived for various social groups (for example, single working age adult, lone parent, couple with children, pensioner). The authors clarify that this approach is not intended to replace official measures of poverty based on fractional income but will *"...help to 'ground' them in an informed estimate of how much income households need to avoid hardship"* (p.p. 4). They demonstrate this by showing that individuals defined as poor based on the conventional measure (60 per cent of median income) have incomes which fall much below the minimum income standards defined by the study. For example, a couple with two children requires 73 per cent of median income and a lone parent with one child requires 71 per cent of median income for an acceptable standard of living. In terms of social policy, such an approach is also useful for assessing the adequacy of the minimum wage and social benefits. A key limitation is that the thresholds need to be uprated every year to allow for changes in the cost of goods, and rebased every few years to accommodate changes in living standards.

3.3.3 Income versus deprivation

Ringen's idea of measuring poverty directly was pursued in studies of Irish data (Callan et al., 1993; Nolan and Whelan 1996), which confirmed that low income and deprivation were not necessarily correlated. This could be due to, *"personal preferences and the efficiency with which resources are converted into living standards"* (Berthoud and Bryan, 2008, p.p. 15). Recent British research has shown that despite a strong relationship existing between low income and an index of hardship[11], two out of five families in income poverty were not in hardship (Vergeris and Perry, 2003). Despite these inconsistencies, the sole use of indicators of deprivation is questionable given that measurable items are market-based goods, thus, income is central to defining standards of living. Moreover, in Mack and Lansely's study, income is used to confirm that deprivation is the result of a lack of financial resources rather than choice, which emphasizes the importance of income in measuring poverty. A focus on direct measures of living standards does not capture underlying income poverty. For example, the onset of income poverty and a fall in living standards may not be correlated due the availability of 'safety nets'

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[11] For example, findings from the *Families and Children Study* (FACS) (Vergeris and Perry,2003) show that a reduction in poverty levels between 1999 and 2001 through increased Income Support and Child Benefit rates were associated with an increase in the living standards of low-income families. Based on an index of hardship (comprised of items such as housing conditions, essential items, health, and financial well-being) 41 per cent of out-of-work families were experiencing deprivation in 1999. By 2001, this had decreased to 28 per cent among out-of-work lone parents and 22 per cent among the couples. During the same period, the proportion of children experiencing hardship fell from 67 to 53 per cent.

such as government benefits, help from family, charities, drawing upon savings, or entering into debt. In addition, the length of time spent in poverty may explain the difference between those who suffer deprivation as a result of low income and those who do not. It is difficult to compare deprivation across different countries as the items for inclusion in an index are subject to local preferences. Over time, absolute measures of deprivation could suggest that poverty has disappeared due to an increase in overall living standards, however, poverty as measured by low income may still exist (Berthoud and Bryan, 2008). This implies that perceptions of deprivation need to be re-assessed in tandem with rising living standards. Finally, many factors that are included in multiple deprivation approaches are correlates or outcomes of poverty when income is used as the indicator of poverty.

Part II Data and definitions

The aim of the following sections is to survey the data requirements and available survey data for the study of poverty dynamics, and to introduce the key definitions used in this thesis.

3.4 Appraisal of data sources for the study of poverty dynamics

The dynamics of poverty tends to be investigated using panel data so that the income trajectories of the same individuals or households can be analysed over time. This section appraises what information is needed for such an analysis and what can actually be measured given available British data. Ideally, a detailed and repeated measure of family income from all sources is required for each child. The data should be nationally representative and cover the whole of the income distribution. Furthermore, the data should span all stages of childhood through to adulthood in order to capture the experience of poverty across the life-course. In reality, however, no British survey meets all of these requirements.

3.4.1 Birth Cohort Data

Britain has a long tradition of cohort studies, which follow members from birth, through the childhood years and into adulthood. The four major studies are:

i. the 1946 National Survey of Health and Development (NSHD);
ii. the 1958 National Child Development Study (NCDS);
iii. the 1970 British Cohort Study(BCS70);
iv. the 2000 Millennium Cohort Study (MCS).

The main objective of these surveys has been on child development and the factors affecting it, for example, obstetric services, the quality of life in the first week of life, and foetal malnutrition. Over the years, the focus has increased to include socio-economic, demographic, health and attitudinal measures. Despite the wealth of data, a major drawback is the high attrition rate of respondents - just over 40 per cent of the initial BCC70 sample was interviewed in all of the childhood waves up to age 16 and at age 30. In addition, the cohort studies were not conceived with the intention of accurately and consistently measuring incomes. With regards to the NCDS, no income data was collected at birth and a question was asked on whether respondents faced 'financial difficulty', which is an imprecise measure for the study of poverty dynamics due to its subjective nature. Moreover, the relative infrequency of data collection restricts the analysis of poverty dynamics. [12] Despite the lack of income measures, there has been a wealth of research using these data to examine the persistence of advantage or disadvantage across generations and to examine childhood factors that predict outcomes in adulthood. [13]

3.4.2 Panel Data

In 1991, the British Household Panel Survey (BHPS) was established, which specifically attempted to measure income on an annual basis. This data source has a number of advantages over the cohort studies. Firstly, the BHPS yields frequent and more detailed information on parents' income, hence, it is possible to observe change directly. In addition, the data provide a better reflection of contemporary society, in contrast to the cohort studies which refer to previous generations of children who experienced a different economic, social, and political climate. For example, two salient changes that are more common among BHPS members than NCDS members are employment of mothers and lone parenthood.

A shortcoming of the BHPS is that it is relatively short in length (the 17th wave of data was released in February 2009), with the implication that income trajectories from childhood to adulthood cannot be observed. However, many of the panel surveys in industrialised countries are short in length. Exceptions to this include the US's Panel Survey of Income Dynamics (PSID), which began in 1968, and the German Socio-Economic Panel (GSOEP), which started in (West) Germany in 1984. As with the cohort data, panel surveys share the problem of respondents dropping out of the survey, however, bias can be alleviated through the use of weighting.

3.4.3 Administrative data

The study of poverty dynamics can also be undertaken using administrative records of claimants receiving means-tested benefits, such as income-support or housing benefit (Noble et al.,1998; Ashworth et

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[12] For example, data for NCDS cohort members was collected at age 0, 7, 11, 16, 23, and 33; BCS data was collected at age 0, 5, 10, 16, 26, and 30.

[13] Section 2.3 discusses some of the findings from this research.

al.,1997). The advantage of administrative data is that it is an up-to-date and economical source of data as it is already routinely collected, and so does not suffer the problem of sample attrition. The claiming of benefits can be thought of as a proxy for poverty, hence, analysis of administrative data does not rely on arbitrary poverty lines. The main drawbacks are that these data do not elicit information on ex-claimants and whether the individual or family escaped poverty by ceasing to claim. In addition, administrative data only captures those who are claiming and not those who are eligible to claim but do not. Since benefits are claimed by adults and not children, it may not be possible to trace individual children across time.

3.5 Description of the BHPS

The analysis in this thesis is based on longitudinal household survey data from the British Household Panel Survey (BHPS), covering waves 1-12 (survey years 1991-2002). In autumn 1991, the BHPS interviewed a nationally representative sample of 5,500 private households, comprising of approximately 10,000 full adult interviews (i.e., those aged 16 or above). The initial selection of households for inclusion in the panel survey was made using a two-stage clustered probability design and systematic sampling, and is approximately an equal probability of selection method (epsem) design. The same individuals have been re-interviewed each successive year. If they leave their original household to form new households, then all the adult members of the new households are also interviewed as part of the survey. Children in the original households are also interviewed once they reach the age of 16. The sample design ensures that the data collected are broadly representative of the population of Britain as it changed through the 1990s.

As with any survey, there are sample selection problems with the BHPS as some eligible individuals do not yield an interview. To mitigate against biases caused by differential non-response at wave 1, the obtained sample is weighted to reflect population characteristics as closely as possible such as age, sex, type of dwelling, etc. A further problem of non-response specific to panel data arises because respondents at the first wave may fail to give an interview at subsequent waves, so that the remaining sample may no longer be representative. This process is known as attrition. The wave-on-wave response rate was about 88 per cent for wave 1 to wave 2, and over 90 per cent thereafter. Longitudinal weights, which use more detailed information about individual characteristics available from the most recent wave, are used to counter such attrition bias for longitudinal analysis. [14]

[14] For a detailed discussion of the BHPS sampling, representatives, weighting and imputation procedures, see Taylor (2001) and Lynn et al., (2006).

3.6 Definitions used in this thesis

3.6.1 Definition of a child

A child is defined according the HBAI definition, that is, a person who is aged under 16, or aged 16-18 and in full-time secondary education, not married, living with parents and not a parent themselves.

3.6.2 Unit of analysis

The unit of analysis in this thesis is the individual, rather than the household to which he or she belongs. Following conventional practice, total household income is attributed equally to each member. This leads to the assumption that all individuals within the household pool their incomes, share equivalent living standards and are equally likely to be poor.

In the conference briefing, 'Measuring Poverty: Seven Key Issues' (ISER, 2008), Bennet identified the distribution of resources within the household as one of the key issues in measuring poverty. She argues that households vary in the extent to which members share and pool resources, thus individuals within the 'black box' of the household vary in their experience and depth of poverty. At the same time, she acknowledges that it is difficult to measure this phenomenon quantitatively given that large-scale surveys do not provide systematic measures on the extent of intra-household income distribution. [15]

3.6.3 Income

The principal indicator of child welfare used in this thesis is income, specifically, net current income, which is expressed in pounds sterling per week in January 2003 prices. To account for differences in household size and composition, incomes are deflated by a household-specific equivalence scale (McClements scale). This definition is consistent with national statistics on the income distribution and poverty, which are reported annually in the HBAI publications.

The household income variable available in the official BHPS release files refers to gross income, that is, income prior to the deduction of income tax, National Insurance, pension contributions and local taxes. However, a more appropriate proxy for individual well-being is represented by the *net* income of the

[15] Empirical studies on the direct expenditure on children suggest heterogeneity in the patterns of intra-household income distribution, which can lead to 'hidden poverty' (Lister, 2004). Findings from the Small Fortunes Survey, for example, highlight the extent to which parents go without necessities to provide for their children. As many as one mother in twenty sometimes went without food to meet the needs of their child. Lone mothers on Income Support, in particular, reported making sacrifices: they were 14 times more likely to go without food, and over three times more likely to go without a holiday than mothers in two parent families not on Income Support (Middleton et al., 1997).

individual's household. Household net income is defined as the sum across all household members of: cash income from all sources (income from employment and self-employment, returns from investments and savings, returns from private and occupational pensions, and other market income, plus cash social security and social assistance receipts plus private transfer) minus direct taxes (income tax, employee National Insurance contributions) and occupational pension contributions. The derived net income variables were constructed using definitions adopted by the Department of Work and Pensions in the HBAI reports. Net household income variables have been provided by Bardasi and Jenkins (2004), as an unofficial supplement to the BHPS data, and have been employed in this thesis.

In line with the HBAI series, the time period to which income refers to is current (rather than annual) income, that is, each household's income from all income components in the month prior to the annual BHPS interview. Theoretically, annual income provides a better reflection of household welfare than current income as transitory fluctuations in income can be smoothed over in the short-term through savings or credit. However, using the BHPS, Böheim and Jenkins (2000) demonstrate that the shapes of the annual and current income distributions are very similar, with estimates of the proportion of the population with low income differing by at most one to two percentage points. The authors posit that the differences are small because the current income measure includes information about usual pay rather than last pay for employees in the household, and income from investments and self-employment. Thus, some income smoothing is already incorporated, and this will moderate differences between current and annual income measures.

To remove the impact of inflation on the picture of poverty dynamics, all net income values were converted to January 2003 prices using a RPI index as the deflator (see Bardasi and Jenkins, 2004 for further details). This ensures that incomes are comparable across all waves and give a measure of real living standards.

In order to allow comparisons of the living standards of different types of households, income is equivalised to take into account variations in the size and composition of the households. This is because a family of several people requires a higher income than a single person in order for both households to enjoy a comparable standard of living. The 'McClements Before Housing Costs' equivalence scale has been employed in the analysis to aid comparability with official government income statistics. The scale takes a childless married couple as the benchmark, with a value of one, and differentiates between adults and children, and between children of different ages. For example, a single person would require 61 per cent of the income that a childless couple would require to achieve the equivalent standard of living. [16]

3.6.4 Definition of poverty

This thesis adopts a relative measure of poverty in line with official reporting of poverty statistics. As discussed in Section 3.2, relative poverty is often the preferred measure, both nationally and cross-nationally because it examines economic deprivation subject to a household's social and economic context. Median rather than mean income is used since the latter can be influenced by outlying observations given that the income distributions are highly skewed.

Whilst poverty is defined as a binary variable throughout although it is acknowledged that, in reality, the depth and severity of poverty varies across individuals. However, one reason for using a binary variable is that poverty policies are often evaluated according to a headcount measure. To account for the differential experience of poverty, three poverty lines are used that vary according to the location of individual incomes in the income distribution (50, 60, and 70 per cent of median income). Thus, this thesis allows findings from the analysis of the BHPS to be compared with HBAI figures and European studies. Table A3.2 in the Appendix reports all three poverty lines from 1991 to 2002.

It is important to note that whilst the term "child poverty" is widely accepted, it is also debatable (Mayer, 2000, p.p. 20). Children are neither income providers nor responsible for their status. They merely experience the consequences of living in poor households. Furthermore, characteristics that are related to the risk of children's poverty are characteristics that pertain to their parents or household, for example, education, employment, disability. Hence, terms such as "childhood in poverty", "children in poor families", or "children living in poverty" may be more apt.

3.6.5 Definition of the dynamics of poverty

The term 'dynamics of poverty' is used in this thesis to mean the heterogeneous patterns of poverty across different time dimensions, namely, point-in-time, short-term transitions, and long-term trajectories. It encompasses the duration of poverty over time, the flows into and out of poverty, and the processes which result in individuals spending different lengths of time in poverty. It is used interchangeably with the term 'poverty dynamics'.

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[16] See DWP, 2006, Appendix 2 for further details of the McClements Scale definition.

3.6.6 Sample size

Although the focus of the analysis is on child poverty, the thesis compares the children's sample with the whole sample. The unbalanced panel is comprised of individuals who are not necessarily observed in each year. Some may have entered the panel after wave 1(1991) or left prior to the end of wave 12 (2002). The unbalanced panel is composed of 18,277 individuals, of which 5209 are children. This gives a total of 124,743 person-year observations for all individuals and 29,790 for children. Children represent about 24 per cent of the total number of persons (see Table A3.1 for sample sizes across waves). The balanced panel (that is, the sample in which individuals are present in every panel wave) consists of 4,441 individuals of which 519 are children.

3.7 Conclusion

This chapter has described a variety of poverty line definitions. The essential difference between them is found in the formulation of the relationship with the standard of living in society. An absolute standard defines poverty by reference to the actual needs of the poor and not by reference to the expenditure of those who are not poor. Defined in these terms, a family might be considered poor if it cannot afford to eat. A limitation with this is that by employing a minimal definition of basic needs, a whole range of other problems that impact on people's lives in serious ways are ignored. A relative definition of poverty attempts to rectify this shortcoming by stating that families experience poverty not only when they are unable to 'live' or 'get by', but also when they lack the material and non-material resources to meet socially recognised needs and to participate in the life of the community and wider society. Despite the rivalling debates and developments surrounding poverty measurements, no indisputable threshold exists below which maintaining an acceptable standard of living would not be possible. The most likely reason is because the kinds of resources required to avoid poverty vary widely among individuals and are contingent upon societal and cultural factors. Part II discussed the practical data requirements for a study of poverty dynamics and surveyed the available data sources. It concluded with a statement of the definitions adopted for use in the empirical analysis in subsequent chapters. In order to aid comparability with existing national and international studies, a relative definition of income poverty is adopted.

Chapter 4 Cross-sectional Trends in Child Poverty

4.1 Introduction

The traditional method of quantifying the extent of poverty at a particular point in time is to calculate the head-count ratio, or the percentage of households or individuals with incomes lower than a defined poverty line. Head-count ratios are measured annually in the HBAI reports to show how poverty is changing over time and how it is distributed among different sub-groups. Chapter 2 discussed the shortcomings of this static approach, however, a cross-sectional perspective is important for contextualising the longitudinal patterns of poverty that are analysed in subsequent chapters.

This chapter considers two types of poverty comparisons, namely, cardinal and ordinal. Cardinal comparisons involve comparing numerical estimates of indices, whereas ordinal comparisons rank poverty across income distributions, without quantifying the precise differences that exist between these distributions. The main advantage of the former is the ease with which values of the indices can be compared across distributions, however, they are sensitive to the choice of arbitrary measurement assumptions (such as the relative weight given to different parts of the distribution or the poverty line used) and the choice of the index itself, which may result in different estimates of poverty. Ordinal comparisons, on the other hand, do not yield a numerical value, but only rank distributions to ascertain the sign of the differences across these two distributions. As will be demonstrated, ordinal rankings are robust to a number of measurement assumptions. For example, ordinal poverty orderings can often rank poverty over general classes of possible indices and wide ranges of possible poverty lines.

The remainder of the chapter is organised as follows. Section 4.2 provides an overview of the literature on how child poverty differs across various socio-economic and demographic variables. Methods for analysing poverty using cardinal and ordinal techniques are discussed in Section 4.3. The research hypotheses are set out in Section 4.4. Section 4.5 presents the analysis on cross-sectional trends in poverty. The final section concludes.

4.2 Previous literature

4.2.1 The characteristics of children in poverty

Not all children in poverty experience the same risk. Since 1999/2000, the annual HBAI publications have presented poverty rates disaggregated by socio-economic and demographic factors. A limitation of these publications is that they provide no objective measures of the depth and severity of poverty, thus, it is unclear to what extent the poorest of the poor and particular sub-groups have improved their economic position over time beyond headcount measures.

With regards to the characteristics of the poor, a consistent finding from the HBAI reports is that children have a particularly heightened risk of income poverty if they belong to one of the following five categories:

i. lone-parent families
ii. workless families
iii. large families – three or more children
iv. families containing one or more disabled persons
v. rented accommodation, particularly social rented accommodation

The child poverty statistics are not stratified by gender of the household head in the HBAI publications, however, the literature also identifies female headed households as an important factor for raising the risk of child poverty.

This section expands upon how each of these factors is associated with child poverty. It is important to bear in mind that various risk factors overlap in important ways, for example, in the interface between work status and lone parenthood. Information about the incidence or risk of poverty amongst different groups does not in itself elicit the causes of poverty, however, it draws attention to the close associations between poverty and wider inequalities in society.

i. Lone parenthood

Family structure is associated with a greater likelihood of child poverty. For example, 37 per cent of children in lone parent households live in poverty, compared with 18 per cent of children in couple households (DWP, 2008). The number of children living in lone parent households is steadily increasing, leading to a greater number of children affected by poverty: in 2007, the proportion of lone parents as heads of households (12 per cent) was treble that in 1971 (4 per cent) (ONS, 2008).

While caring for children affects all mothers' ability to participate in paid employment, relatively fewer lone mothers work: in 2000, lone-parent families were over nine times as likely as couple families to have no parent in work for any hours (47 per cent compared with 5 per cent) (Barnes at al., 2004). Compared with children from couple families, children from lone parent families are less likely to be in good health and more likely to have contact with the police. However, when the work status and income of families is taken into account, most of the differences in disadvantage between the children of lone parent and couple families disappear, suggesting that economic status is a stronger predictor of disadvantage rather than family type (Vergeris and Perry, 2003).

ii. Workless and working poverty

Low income is the primary cause of poverty, which is largely determined by employment status, wages and benefits. The HBAI statistics reveal that worklessness (defined as no working-age person in the household working at least one hour a week) is the biggest risk factor for poverty among all the characteristics considered in the reports: in 2006/2007, 63 per cent of children in workless households were poor – three times the rate of poverty for the child population as a whole (22 per cent) (DWP, 2008).

Paid work itself is not a guarantee of avoiding poverty. Low wages, part-time work and not having two adults in employment from a couple household increase the risk of poverty: over a quarter of all child poverty (29 per cent) occurred in households where at least one parent was doing some paid work. Between 1996/7 to 2006/7, the proportion of poor children in workless families fell from 55 per cent to 47 per cent, whilst those in working families increased from 45 per cent to 53 per cent. Whether a child experiences workless or working poverty is associated with whether they belong to a lone or couple family. Table 4.1 shows the changes in the composition of poor children by work status and family type.

Table 4.1: Composition of poor children by family type and parental employment status (%), 1996/7 to 2007/8

	1996/1997			2006/2007		
	Working	Workless	Total	Working	Workless	Total
Couples	39	21	60	45	15	60
Lone	6	34	40	8	32	40
Total	45	55	100	53	47	100

Source: DWP (2008) Table 4.3

In 2006/7, half of all poor children lived in a household in which someone was working, up from 45 per cent a decade ago. Over the same period, there has been a reduction in the proportion of poor children living in workless households, from 55 per cent to 47 per cent. In the most recent year, 45 per cent of poor children belong to working couple households in contrast to 8 per cent of lone parent children. One third (32 per cent) of poor children belong to workless lone parents, which is almost twice the figure for children in couple families (15 per cent). Thus, worklessness is a more significant factor underpinning child poverty in lone parent families, whereas working poverty is a more important factor for child poverty in couple families.

iii. Large family size

An increase in family size is associated with an increase in the risk of poverty. This is likely to be due to an increase in the cost of consumption associated with each additional child and the reduction in household employment intensity due to caring responsibilities. In 2006/7, 33 per cent of children in families with 4 or more children were poor. This is almost twice the poverty rate for children in one-child families (18 per cent) (DWP, 2008). Bradshaw et al. (2006) explored the characteristics of child poverty in large families (defined as at least 3+ children in a family) using the Family Resources Survey, the Millennium Cohort Study and the Families and Children Survey. The aim of the study was to investigate whether it is family size itself that explains the high risk of child poverty in large families, or whether there are other factors associated with having many children which are also associated with a high risk of poverty. They found that factors such as a parent being disabled, an ethnic minority, unemployed, having low educational attainment, and having their child at a young age were associated with children belonging to large families. Whilst these factors are themselves also associated with and increased the risk of child poverty, the authors found that there was a large "family effect" independent of other characteristics. A child in 4+ child family is between 170 per cent and 230 per cent more likely to be poor than a one-child family, other things being equal.

iv. Disability

Living in a household with a disabled adult increases the average risk of child poverty from 22 per cent to 33 per cent (DWP, 2008). Some disabled adults face barriers to employment due to lower than average educational qualifications, while in many cases having a disability affects their ability to gain work, either because of impairment or because of negative attitudes from employers. 60 per cent of disabled people of working age are employed, compared to 15 per cent of non-disabled people (Palmer, 2006). In 2007, 24 per cent of disabled people aged 16-24 had no qualifications at all, compared to 13 per cent of their non-disabled peers. As well as affecting one's chances of earning income from employment, having a disability also increases the risk of material deprivation, as the higher costs associated with many forms of disability mean that the same amount of income allows disabled people to consume fewer goods and services than non-disabled people (Preston, 2006). The birth or diagnosis of a disabled child is considered as a 'trigger event' for persistent poverty (Jenkins and Rigg, 2002). This is associated with the continuity of poor life chances for disabled children, including a greater likelihood of having no qualifications, living in social housing, reliance on benefits, and lower earnings than non-disabled people (Flaherty et al., 2004).

v. Housing tenure

There is a strong relationship between housing tenure and child poverty, with the rate of child poverty being the highest among children living in social rented housing and, to a lesser extent, among children living in private rental housing. Almost half (47 per cent) of all children in social housing and 1 in 3 (27 per cent) in private rental housing were poor in 2006/07. The rate among children in owner-occupied housing was only 1 in 7 (14 per cent) (DWP, 2008). According to Hills (2007), the social rented sector is characterised by disproportionately higher levels of unemployment amongst its tenants than amongst the population as a whole. This is linked more to the tenant profile rather than a disincentive to work created by social rented housing. For example, lone parents and those with long term sickness or disability tend to be concentrated amongst social sector tenants, and it is these groups who find it hard or are unable to go out to work.

vi. Women and poverty

Children's experience of poverty is both shaped by, and linked to, women's poverty. The child poverty statistics are not stratified by gender of the household head in the HBAI publications, however, for the whole population, 18 per cent of women live in poverty, compared to 16 per cent of men (DWP, 2008). These figures, however, obscure the real extent of women's vulnerability to poverty, as survey data cannot take account of the unfair distribution of resources within households. Women's greater vulnerability to poverty is due in part to the difficulties of combining work and caring responsibilities. As well as continuing to have primary responsibility for children's welfare in the majority of households, women are far more likely than men to be carers of elderly relatives, which affects their capacity to undertake paid work and so increases their risk of living below the poverty line. Women are also more exposed to poverty because they are more likely to be lone parents and so face greater obstacles to combining work and childcare responsibilities.

The gap between men's and women's education and training has been eroded over recent decades, with young women today outperforming their male counterparts. Despite this, gender inequalities in pay still persist. An explanation for the gradient in incomes is that jobs which are disproportionately done by women (such as childcare, catering and cleaning) continue to be less well-paid than those in other sectors, and women are more likely than men to be in low-paid, part-time employment. The Women and Work Commission (2006) identifies three main factors sustaining the gender pay gap: part-time working, occupational segregation and women's labour market issues, such as childcare, which act as barriers to women's chances of entering and progressing in the workplace.

4.3 Methods for aggregating the extent of cross-sectional poverty

In order to analyse trends in poverty over time, information on income needs to be aggregated into a summary measure. This section reviews and critiques some of these cardinal indices. As the cardinal approach is subject to arbitrary measurement assumption, Section 4.3.2 goes on to consider ordinal comparisons using the technique of stochastic dominance.

4.3.1 Cardinal measures

In order to evaluate the different indices, Sen (1976) argued that they should be consistent with a set of desirable criteria, and proposed a set of axioms by which to judge these measures. Subsequent debates that ensued from Sen's work gave rise to the development of further axioms. Hagenaars (1991) and Zheng (1997) have summarised these properties, some of which include:

i. Pigou Dalton Transfer principle: A pure transfer of income from a person below the poverty line to anyone who is richer must increase the poverty index.
ii. Monotonicity: The poverty index should be sensitive to the incomes of the poor. A reduction in income of a person below the poverty line must increase the index.
iii. Focus: A change in the income distribution of the non-poor should not change the poverty index.
iv. Transfer sensitivity: When there is transfer of income from a poorer to richer person, the increase in the index must be greater the poorer is the poor person
v. Population homogeneity: If two or more identical populations are pooled, the poverty index should not change.
vi. Additive decomposability: Aggregate poverty within a population should be a weighted mean of sub-group poverty, with weights equal to the population shares.

There is a wealth of indices for aggregating poverty. Whilst these axioms are ethically agreeable, not all poverty measures satisfy them. A fundamental division in the literature on poverty measurement is between simple (but commonly used) headcount statistics that simply seek to count the poor, and more complex distribution-sensitive measures that quantify the degree of their poverty.[17] The earliest and most widely used measure of poverty is the headcount ratio *(H)*, which measures the proportion of people in the population with incomes below a given poverty line. Let $\mathbf{y} = (y_1, y_2, \dots, y_n)$ be the vector of individual incomes of a population of size n arranged in ascending order. If z is the poverty line, then an individual is defined as poor if $y_i \leq z$. The number of poor individuals is defined as q. H is expressed as:

$$H = \frac{q}{n} \tag{1}$$

H satisfies the focus axiom (the poverty rate increases (decreases) if more (less) individual incomes fall below the poverty line) but violates the transfer and monotonicity axioms as it disregards the extent of income shortfall below the poverty line and the distribution of income among the poor. If a transfer of income from a poorer to richer person (both of whom start with incomes below the poverty line) enables the latter to cross the poverty line, *H* will fall, however, it takes no account of the effect on the individual who remained the below the poverty line and became poorer (Osberg, 2001).

The average poverty gap ratio of the poor *(PG)* remedies the lack of information below the poverty line by measuring the percentage average shortfall of income of the poor relative to the poverty line. Thus, it measures how poor are the poor. In notational terms, let the income gap *(I)* be the income shortfall of a poor person from the poverty line, thus the vector of income gaps is defined as $I = (x_1, x_2, \dots, x_q)$ where each poor individual's income gap ratio is:

$$x_i = \frac{z - y_i}{z} \qquad i = 1, 2, \dots, q \tag{2}$$

The non-poor have zero income gap ratios. *PG* is the mean income shortfall of the poor divided by the poverty line:

$$PG = \frac{1}{n} \sum_{i=1}^{q} \left(\frac{z - y_i}{z} \right) \tag{3}$$

PG satisfies the monotonicity axiom and increases (decreases) if income shortfalls from the poverty line are larger (smaller). A limitation of *PG* is that it is not sensitive to the distribution of income among the

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[17] Atkinson (1987), Foster, Greer and Thorbecke (1984), Kakwani (1980), and Seidl (1988) have provided surveys on these measures.

poor. For example, if a transfer from a poorer to a richer person (both of whom are poor) leaves the latter below the poverty line, the aggregate shortfall will not change as the increase in the poorer person's shortfall is offset by the decrease in the richer person's shortfall.

The inadequacies of the *H* and the *PG* were addressed by Sen (1976), who constructed an index *(S)* that is the weighted average of *H* and *PG,* with the weights being the Gini coefficient of inequality among the poor, G_P. The weights give the rank of a person among the poor, with the poorest person receiving the highest weight and the least poor person receiving the lowest weight. *S* is expressed as:

$$S = H(G_P) + PG(1 - G_P) \tag{4}$$

As such, *S* satisfies the focus, monotonicity and transfer axioms as it takes account of the extent of poverty through *H*, the shortfall of income through *PG*, and inequality below the poverty line through G_P.

An important aspect of poverty analysis is to identify sub-groups who have a heightened risk of poverty and who make a relatively large contribution to aggregate poverty. A limitation of the Gini coefficient, and thus *S*, is that it does not satisfy the axiom of additive decomposability. Foster, Greer and Thorbecke (1984) proposed a class of class of indices *(FGT)* which have an additive structure:

$$P_\alpha = \frac{1}{n}\sum_{i=1}^{q}\left(\frac{z - y_i}{z}\right)^\alpha, \quad \alpha \geq 0 \tag{5}$$

where α is a parameter which gives greater weight to income shortfalls further away from the poverty line. When $\alpha = 0$, P_0 is equivalent to *H,* the headcount ratio. If α =1, P_1 is the poverty gap ratio, *PG.* The value α =2 gives rise to the squared poverty gap *(SPG)* or P_2. The greater the value of α, the more sensitive the measure is to the poverty of poorest person as greater weight is given the lower part of the income distribution. By weighting the income gaps by the gaps themselves, greater weight is accorded to poorer individuals, thereby incorporating distributional sensitivity amongst the poor.

Ravallion (1994) suggested that P_0 measures the "prevalence" of poverty, P_1 the "depth" of poverty, and P_2 the "severity" of poverty. The importance of measuring the depth of poverty has been articulated by Brewer et al. in the Institute for Fiscal Studies' annual commentary on poverty and inequality in Britain:

> "*...the depth of poverty is a very important issue: we should be more concerned about those a long way into poverty than those just below the poverty line , and tackling deep poverty might require different policies from those that aim simply to move people from just below the poverty line across it*" (Brewer et al., 2004, p.p. 35).

Despite their theoretical shortcomings, the headcount ratio and the poverty gap are highly popular measures and have public resonance as they are readily interpretable and simple to communicate, unlike more complex measures that are more theoretically sound (Myles and Picot, 2000). Despite the lack of intuitive appeal, the severity index may have more desirable policy implications in terms of targeting resources more equitably. A further advantage of this class of indices is that aggregate population poverty can be decomposed into *m* mutually exclusive sub-groups, where each sub-group is denoted as *j*. Examples of these include gender, education status, employment status, etc. This is expressed as:

$$P_\alpha = \sum_{j=1}^{m} \frac{n_j}{n} P_{\alpha j} \tag{6}$$

Thus P_α is a population-weighted mean of the sub-group poverty measures. Table 4.2 summarises the properties of the poverty indices discussed in this section.

Section 4.4.1 highlights that the axiomatic approach does not succeed in identifying any single index as the "best" measure, however, it is useful in revealing the ethical principles underlying the various measures.

Table 4.2: Summary of poverty indices

Poverty measure	Formula	Description
P_0 Headcount index *(H)* The *prevalence* of poverty: how many poor people	$P_0 = \frac{1}{n}\sum_{i=1}^{q}\left(\frac{z-y_i}{z}\right)^0 = \frac{q}{n}$	P_0 measures the proportion of the population whose income lies below the poverty line, *z*. Limitation: a transfer from a poor to less poor person (both who start with incomes below *z*) does not change P_0.
P_1 Poverty gap index *(PG)* The *depth* of poverty: how poor are the poor	$P_1 = \frac{1}{n}\sum_{i=1}^{q}\left(\frac{z-y_i}{z}\right)$	P_1 measures the average shortfall between a poor individual's income and the poverty line. Limitation: it is insensitive to the distribution of income among the poor.
P_2 Squared poverty gap index *(SPG)* The *severity* of poverty: greater weight placed on shortfalls of income furthest from the poverty line.	$P_2 = \frac{1}{n}\sum_{i=1}^{q}\left(\frac{z-y_i}{z}\right)^2$	P_2 squares the shortfall between an individual's income and the poverty line, thus attributes more weight to larger shortfalls. Limitation: less intuitive to interpret.
S Sen's measure of poverty	$S = H(G_P) + PG(1-G_P)$	Expresses poverty as a weighted average of *H* and *PG* where the weight is the Gini coefficient of the poor. Limitation: the Gini coefficient is not additively decomposable, i.e., aggregate poverty cannot be broken down into sub-group poverty.

Source: Author

4.3.2 Ordinal comparisons: checking the robustness of poverty estimates using stochastic dominance

This section applies the methodology of stochastic dominance to ascertain whether poverty comparisons can be considered robust to the choice of poverty lines and a wide class of poverty indices. It is based on ordinal comparisons of income distributions ("In which year did poverty *rank* the highest?") as opposed to cardinal comparisons ("What was the *level* of poverty in a particular year?"). Thus stochastic dominance examines the sign of the differences between two distributions rather than their precise numerical value. This technique was initially pioneered Atkinson (1987) and Foster and Shorrocks (1988a, 1988b, 1988c) and has recently been applied to the study of changes in poverty in Ireland (Madden and Smith, 2000), Chile (Ferreira et al. 1998), and a comparative study of gender differences in poverty in ten developing countries (Quisumbing et al., 2001).

Let

$$F_A(y) = \int_0^y f_A(x)dx \qquad \text{and} \qquad F_B(y) = \int_0^y f_B(x)dx \qquad (7)$$

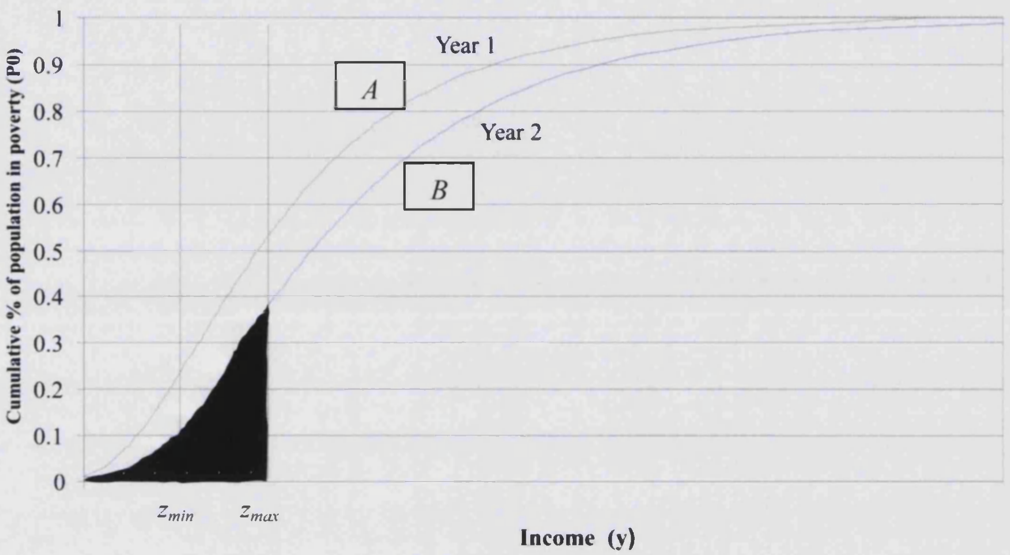
denote two cumulative distribution functions (c.d.fs) where y refers to income. Ravallion (1994) refers to these c.d.fs as "poverty incidence curves" as each point on the curves correspond to the proportion of the population deemed poor (i.e., the headcount index, P_0) if points on the horizontal axis refer to values of the poverty line, z.

With regards to z, it is not necessary to know the precise value for stochastic dominance analysis, however, an upper bound of a reasonable set of poverty lines can be specified, $z_{\max}$ such that y lies within the interval $[0 \quad z_{\max}]$. Atkinson (1987) suggests that stochastic dominance can be analysed within a *restricted* interval of poverty lines, $[z_{\min} z_{\max}]$ which strictly lies within the wider range $[0 \quad z_{\max}]$ in order to avoid conclusions being biased by a small number of observations in the extreme tails of the income distribution. Distribution B first-order dominates distribution A if, for all monotone non-decreasing functions and for all y within the interval of poverty lines:

$$F_A(y) > F_B(y) \qquad \text{for all } y \in [z_{\min} z_{\max}] \qquad (8)$$

First-order dominance covers a wide class of poverty indices that are continuous and increasing in y (Giovagnoli and Wynn, 2009). Figure 4.1 shows hypothetical c.d.fs (or poverty incidence curves) for two distributions, A and B. A lies everywhere above B at all poverty lines, thus, the proportion of the population consuming less than or equal to the amount given on the horizontal axis is lower in B than in A.

Figure 4.1: Poverty incidence curves – first-order dominance



If the incidence curves intersect, as in Figure 4.2, the ranking is ambiguous. It is not possible to state whether one distribution dominates another as the ranking will change depending on the location of the poverty lines. Poverty at z_b is higher in distribution A but at z_a poverty is higher in distribution B. To establish dominance in this case, an option is to restrict the range of poverty lines over which dominance is to be tested. Alternatively, higher orders of dominance can be considered, which cover a smaller class of poverty measures that are sensitive to the shortfall of income from the poverty line, such as poverty gap and squared poverty gap indices.

Second-order dominance covers measures that strictly decreasing and at least weakly convex in the incomes of the poor (Giovagnoli and Wynn, 2009). This includes the poverty gap ratio, P_1. Second-order dominance can be established by comparing the *integral* of the poverty incidence curves (i.e., the area under the c.d.fs). Ravallion (1994) refers to these as the "poverty deficit curves", $D(y)$. Distribution B second-order dominates distribution A, if and only if:

$$\int_0^y F_B(x)dx \leq \int_0^y F_A(x)dx \qquad \text{for all } y \in [z_{\min} z_{\max}] \tag{9}$$

That is, poverty in distribution B is lower than poverty in distribution A if the area under the poverty deficit curve $D_B(y)$ is less than that of $D_A(y)$ for all points up to the maximum poverty line. Figure 4.3

provides a hypothetical representation of this. Second-order stochastic dominance is a concept that is weaker than first-order stochastic dominance as it covers a more restricted set of poverty indices (i.e., those that also satisfy the Pigou Dalton transfer principle). First-order stochastic dominance implies second-order dominance but not vice versa.

If second order dominance also fails to hold, then third-order dominance can be tested by further restricting the admissible poverty measures to those that are sensitive to distribution of poverty. This includes the squared poverty gap P_2 . This is done by comparing the "poverty severity curves", $S(y)$ (Ravallion, 1994), which are defined as the integrals of the deficit curves:

$$\int_0^y D_B(x)dx \leq \int_0^y D_A(x)dx \qquad \text{for all } y \in [z_{\min} z_{\max}] \qquad (10)$$

Distribution *B* third-order dominates distribution *A* if the area under deficit curve *B* is smaller than the area under deficit curve *A*. If third order dominance does not hold, one can continue to test for higher order dominance, however, Ravallion (1994) argues that the interpretation of the increasingly restricted class of poverty measures becomes less intuitive.

Figure 4.2: Poverty incidence curves – ambiguous ranking

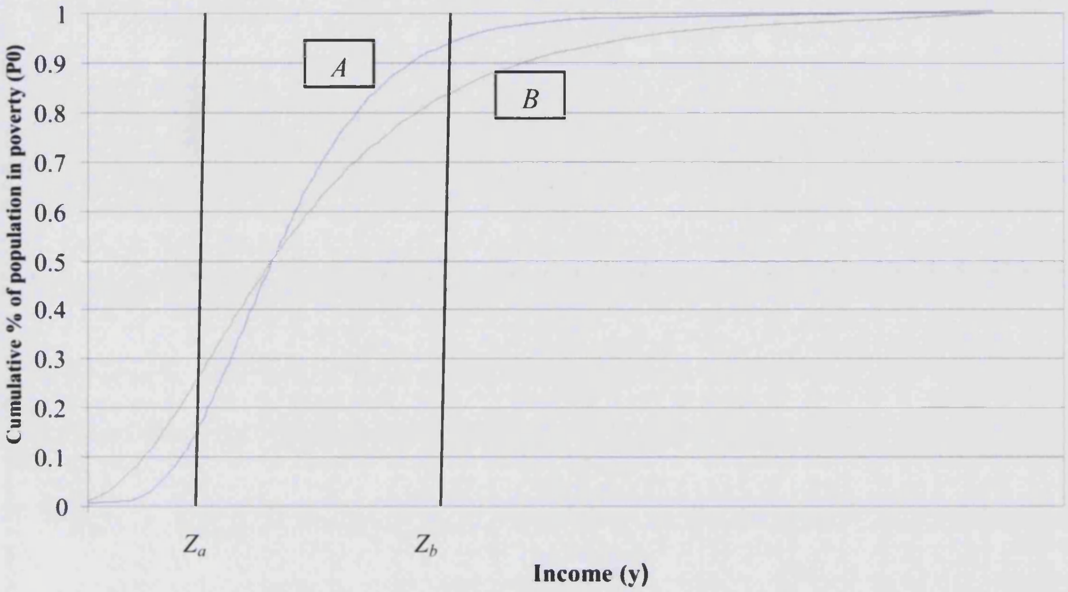
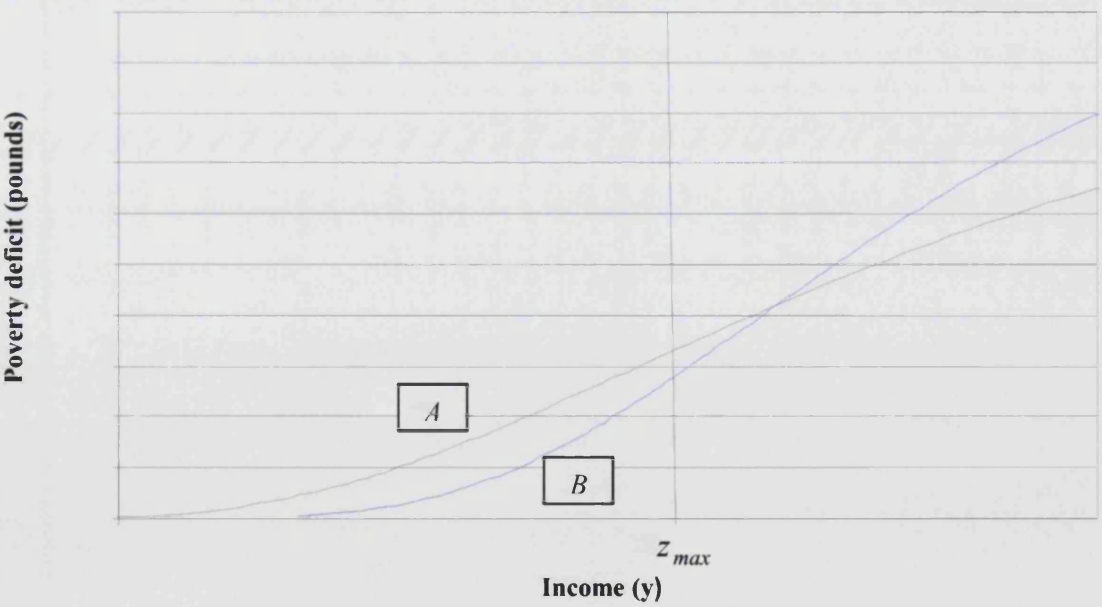


Figure 4.3: Poverty deficit curves – second-order dominance



Source: Author's own

4.3.3 Inference tests

In order to test whether first-order dominance holds, the c.d.fs can be visually inspected to ascertain whether or not crossing occurs for any pair of curves. Whilst ordering may appear clear, the difference may be due to sampling error rather than a true difference in poverty levels. Any observed differences may, therefore, not be statistically significant.

Following Beach, Formby and Thistle (1992) and Davidson and Duclos (2000), *t* statistics are constructed to test the null hypothesis of non-dominance between two distributions[18]. Suppose $\hat{P}_A = \left(\hat{P}_{A,1}, \hat{P}_{A,2}, \ldots, \hat{P}_{A,K}\right)$ and $\hat{P}_B = \left(\hat{P}_{B,1}, \hat{P}_{B,2}, \ldots, \hat{P}_{B,K}\right)$ are vectors of estimates of the headcount ratio (corresponding to c.d.f ordinates) for two independent samples with sample sizes n_A and n_B. Let $\hat{\sigma}_A^2$ and $\hat{\sigma}_A^2$ be the vectors of sample estimators of the variances. The statistical test for equality of the i^{th} elements of the vectors $\hat{P}_A$ and $\hat{P}_B$ is given by:

$$T_i = \frac{\hat{P}_{A,i} - \hat{P}_{B,i}}{\sqrt{\dfrac{\hat{\sigma}_{A,i}^2}{n_A} + \dfrac{\hat{\sigma}_{B,i}^2}{n_B}}} \qquad \text{for } i=1,2,\ldots,K \qquad (11)$$

The null hypothesis of non-dominance is given by:

$$H_{0,i} : \hat{P}_{A,i} - \hat{P}_{B,i} = 0 \qquad (12)$$

Under the null, the test statistic follows and asymptotic normal distribution with zero mean and unit variance. To test for stochastic dominance, the null hypothesis is examined at $i=1,2,\ldots K$ test points on the c.d.fs within the relevant interval of poverty lines, $z \in [z_{\min} z_{\max}]$. If the null is not rejected for all *i*, both distributions are ranked equally (i.e., the observed poverty differences in any two samples are statistically insignificant).

In the case where the null hypothesis is rejected, there are two possible alternative hypotheses, namely, dominance or non-comparability (Beach, Formby and Thistle, 1992):

[18] Linton et al., (2003) provide a method for the testing of stochastic dominance where observations are serially dependent. An example of this is where income distributions are compared before and after a change in policy, such as taxes.

i. Dominance: if there is at least one statistically significant positive (negative) difference between the headcount ratios and no statistically significant differences in the opposite direction, first-order dominance can be declared.

ii. Non-comparability: the poverty incidence curves intersect if there are both positive and negative significant differences between the headcount ratios. In this case, first-order dominance cannot be declared and the second-order dominance approach can be implemented by comparing the ordinates of the poverty deficit curves.

4.4 Hypotheses

Various relationships between the sub-group characteristics and poverty are hypothesised. These will be tested through the decomposition of the FGT indices described in Section 4.3.1. More specifically:

i. Parental composition: As lone parents tend to have lower incomes than couples, the poverty indices are expected to be higher amongst the former group. Couples have a greater propensity for earning (for example, both or one parent working part-time or full-time). As lone parents have been specifically targeted by anti-poverty policies in recent years, it is expected that poverty amongst lone parent children decreased proportionately more than for children belonging to couple families.

ii. Education status of the household: Human capital is in part accumulated via educational attainment, which is a proxy for the effect that the transmission of education-related abilities, experiences and opportunities from parents to children may have on the probability of poverty. It is expected that the lower the educational attainment of the family head, the higher the child's likelihood of poverty.

iii. Economic status: The casualisation of employment through greater opportunities for part-time work and self-employment has provided significant economic opportunities, particularly for married women and lone parents who are more likely than men to work part-time. This can give rise to a number of competing influences For example, the rise in labour force participation particularly for married women has increased their earnings, however, the impact of dual-earner households on poverty is less clear-cut depending on whether it is the spouses of poorer or richer households who increase their economic participation. Whilst it is possible that workless households are protected by state benefits, it is expected that they have higher poverty levels than other employed categories. It is also expected that children belonging to workless households have experienced a reduction in poverty, particularly after 1997, due to the growth in policies to reduce worklessness.

iv. Sex of the household head: The impact of sex on poverty is likely to be influenced through its relationship with lone parenthood (the majority of whom are headed by females), rising educational levels, and the structure of employment. Females are over-represented in part-time work have lower average earning than males, thus, it is anticipated that children belonging to female headed households have a higher but declining level of poverty relative to male headed households.

v. Number of children: Families with large numbers of children are likely to have lower levels of disposable income relative to smaller families, thus it is expected that poverty levels are positively related to the number of children. However, due to greater economic support targeted towards families with children, it is expected that that households with large numbers of children have experienced a decline in the risk of poverty over time.

vi. Age of the head: The probability of poverty is expected to be relatively lower for children belonging to heads who are aged 25-44 due to upward mobility in the head's career compared with younger and older heads. The risk of poverty is expected to be relatively high for children belonging to heads who are 45+, which is likely to mirror the decline in the earnings profile in the final stage of a person's career, the lower possibilities of occupational mobility, as well as important changes in the propensity to work (for example, heath-related problems and inability to work) or in the family structure (for example, death of the spouse).

vii. Disability and long-term illness: Poor health may reduce the numbers of employed individuals in the household if it limits the type or amount of work that can be undertaken. Furthermore, employers may be less willing to hire those who are long-term sick if it affects productivity. On the other hand, the welfare state may be effective in protecting people against the negative economic effects of ill-health and disability.

Table A4.1 in the Appendix provides a definition of the covariates used throughout this thesis. Tables A4.2 and A4.3 in the Appendix give basic descriptive statistics for these variables for the population and children, respectively.

4.5 Empirical results

This section presents analysis of the BHPS using the methods presented in sections 4.3.1 and 4.3.2. This is done in four stages: (i) the income distribution, (ii) cardinal comparisons of poverty across time using the FGT indices (P_0, P_1 and P_2), (iii) ordinal comparisons using Stochastic Dominance analysis to ascertain whether changes in poverty are robust to various poverty line and poverty measures, and (iv) profiles of poverty to show how poverty has changed across various sub-groups of children.

4.5.1 The income distribution

The aim of this section is to analyse the distribution of income in Britain from 1991 to 2002. The changes that occurred in the child population are compared to the population as a whole, which allows conclusions to be made about whether children fared better or worse than average. It also enables the findings on poverty to be contextualised within the changes in income inequality. Although the concepts of poverty and inequality are often studied in tandem, they are distinct from one another. Inequality is a broader concept than poverty in that it is defined over the whole distribution, not only the censored distribution of individuals or households below a certain poverty line. Incomes at the top and in the middle of the distribution are just as important to measures of inequality as those at the bottom.

When individuals in the population are ranked from the lowest to the highest on the basis of their household income, they can be divided into equal sized groups, or quantiles. Division into 100 groups gives percentiles. Thus, the tenth percentile, denoted *P10*, is the income level that divides the bottom ten per cent from the rest, and the median or the fiftieth percentile is denoted *P50.*

In notational terms, let $F\ (y)$ be the c.d.f. for income .The *p*th income quantile ξ_p, which is the share of the population with income less than a given level, is defined by:

$$p = F(\xi_p) = \Pr(y \le \xi_p) \qquad 0 \le p \le 1 \qquad (13)$$

The inverse function of the c.d.f. gives the quantile function:

$$p = \int_0^{\xi(p)} f(y)dy = F(\xi(p)) \qquad (14)$$

Alternatively,

$$\xi(p) = F^{-1}(p) \qquad (15)$$

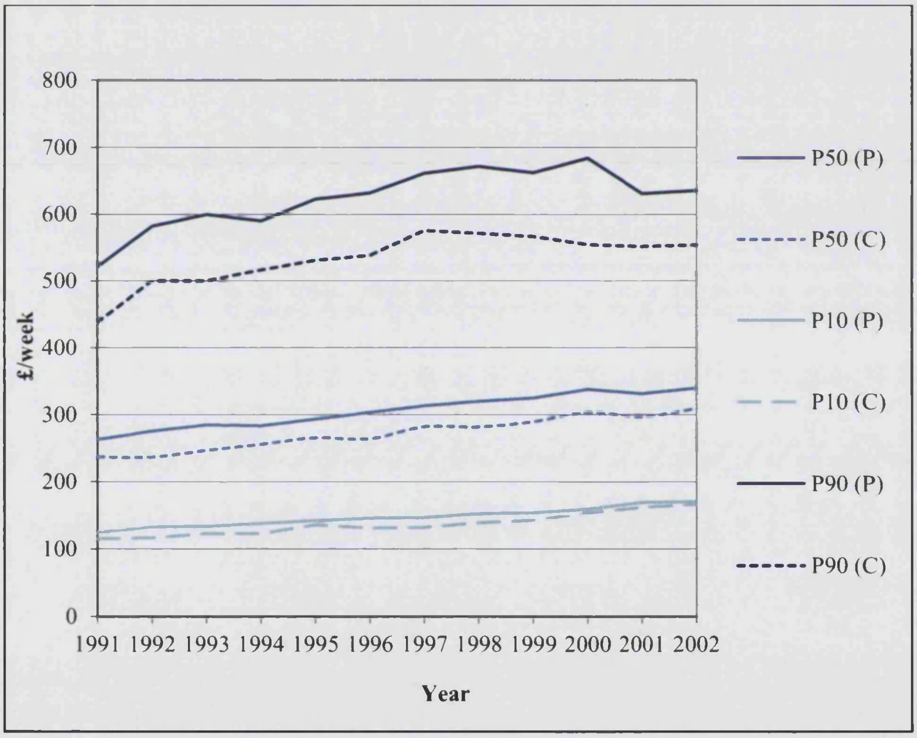
For example, median income, which is defined as the point at which half the population is above and the half below is defined as:

$$0.5 = \int_0^{0.5} f(y)dy = F(0.5) \text{ or } \xi(0.5) = F^{-1}(0.5) \qquad (16)$$

Ratios of selected percentiles, which are called percentile ratios are useful for quantifying the relative distance between two points of the income distribution. For example, the *P90/P10* compares the wealthiest and poorest 10 per cent of the population. As this considers extreme inequalities in the population, it is useful to consider the *P10/P50* ratio, which compares the poorest 10 per cent with the mid-point.

Since 1991, there has been a consistent increase in incomes in Britain, reflecting strong economic growth. The median income *(P50)* of the population increased from £262/week in 1991 to £339/week in 2002. The corresponding figures for children are £237/week and £308/week. Despite the increase in prosperity, the incomes of children have been persistently lower than average. This can be seen in Figure 4.4, which charts changes in real income for various percentile thresholds for both samples. Another feature of the chart is that the relative difference in the incomes of children and all individuals is much smaller for *P90* relative to *P10*.

Figure 4.4: Changes in real income, 1991-2002



Source: Derived from the BHPS 1991-2002[19]
P=population; C=children

Although children have remained less prosperous than the population, different patterns are evident for the *growth* in incomes. Table 4.3 shows the average annual change in income for various quantile groups

[19] All charts and tables based BHPS data (1991-2002) are derived from the author's own calculations unless stated otherwise.

for the periods 1991/1996, 1997/2002, and 1991/2002. It demonstrates the considerable heterogeneity in income growth differentials across time and thresholds. Over the twelve year period (column 3), the largest gain was experienced by the poorest children, whose incomes grew by approximately 3.5 per cent annually. There were marked variations in the nature of inequality during this period. Between 1991-1996, income growth for children was lower than average at all thresholds apart from for the wealthiest children. The smallest gain was made by children with median incomes. This trend was reversed during 1997-2002, whereby children fared better than average at all thresholds. Most notably, the increase in the child lowest incomes was one-and-a-half times that of the counterpart increase in 1991-1996, and eight times that of the highest incomes in 1997-2002.

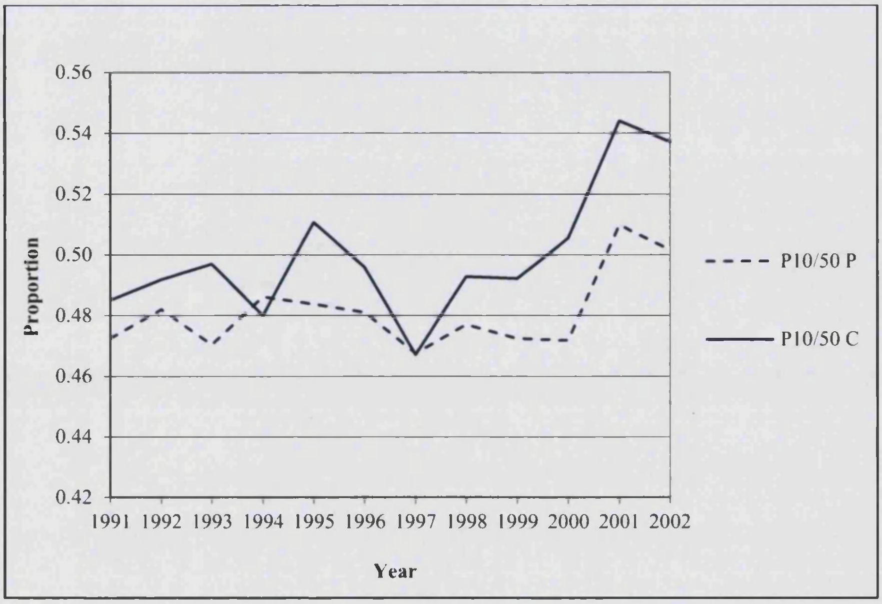
Table 4.3: Average annual real income growth (%), 1991-2002

Threshold	1991-1996	1997-2002	1991-2002
P50 (P)	2.94	1.91	2.38
P50 (C)	2.19	2.73	2.48
P90 (P)	3.99	0.19	1.92
P90 (C)	4.33	0.54	2.26
P10 (P)	3.32	2.63	2.94
P10 (C)	2.74	4.08	3.47

Source: Derived from the BHPS 1991-2002
P=population; C=children

Figures 4.5 and 4.6 show the evolution of the P10/50 and P90/10 percentile ratios over time. Since 1991, the incomes of the poorest 10 per cent have been about half that of the median, however, there has been an upward trend. The P10/50 ratio for children incresed by 11 per cent from 0.48 to 0.54. This was nearly twice the rate of growth for the population as a whole (6 per cent). The increase was most marked after 1997, as the incomes of poorest people grew faster than the median.

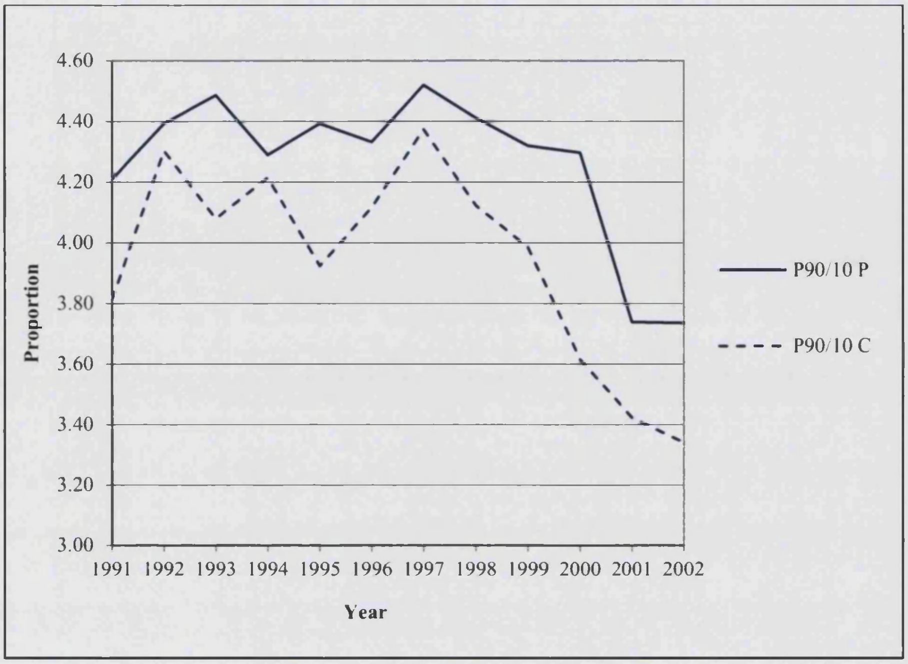
Figure 4.5: Trends in P10/50 ratio, 1991-2002



Source: Derived from the BHPS 1991-2002
P=population; C=children

With regards to the P90/10 ratio, the income of the richest 10 per cent has been approximately four times that of the poorest decile. This finding confirms Brewer et al.'s analysis of the Family Resources Survey (1996/7 to 2002/3) for the whole population (Brewer at al, 2004, p.p. 20). Since 1991, there has been a decline in the ratio, and again, this was most pronounced after 1997. The magnitude of decline was approximately the same for the population and children (12 per cent), however, in recent years, the ratio has converged closer to 3 for children, implying lower than average inequality within this group. These trends can be attributed to the growth in the incomes of the poor after 1997, particularly for children, and a simultaneous decline/stability in the top incomes.

Figure 4.6: Trends in P10/50 ratio, 1991-2002



Source: Derived from the BHPS 1991-2002
P=population, C=children

4.5.2 Trends in child poverty

This section presents analyses on the trends in child poverty using the Foster-Greer-Thorbecke class of indices, namely, i) the headcount (P_0), ii) the poverty gap (P_1), and iii) the squared poverty gap (P_2) indices. The estimates are reported in tables 4.4, 4.5, and 4.6 for all individuals and children at different poverty line thresholds (z=50, 60, and 70 per cent of median income). Figures 4.7, 4.8, and 4.9 chart the trends in the ratios of child estimates relative to all individuals for each index.

i. The headcount ratio: P_0

In general, child poverty as measured by P_0 (as defined in Table 4.2) increased in the early 1990s and declined thereafter to reach its lowest level by 2002 (Table 4.4). The level of poverty is sensitive to the choice of the poverty line and rises with increasing fractions of the poverty line. A robust finding is that child poverty was persistently higher than average over the twelve year period, which confirms the findings from the HBAI statistics (DWP, 2004). According to the 60 per cent measure, 26 per cent of children were living in poverty in 1991 compared with 20 per cent in 2002. The respective figures for the population are 21 per cent and 17 per cent.

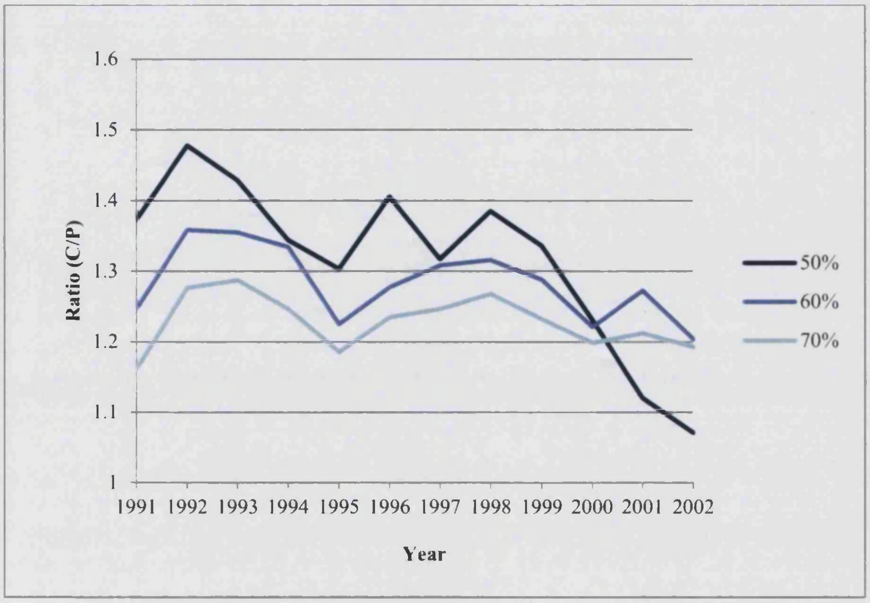
Figure 4.7 highlights the pattern of convergence between child and population poverty levels. The gap between the level of poverty for children relative to all individuals showed the steepest decline at the 50 per cent thresholds, particularly after 1998. In 1991, child poverty was 37 per cent higher than average, however, by 2002, it declined five-fold to a difference of 7 per cent. For the higher poverty lines, the trend is more static. At the 60 per cent threshold, the differential declined from 24 per cent in 1991 to 20 per cent by 2002 over, and at the 70 per cent threshold, the respective figures are 16 per cent and 19 per cent.

Table 4.4: Evolution of P_0, 1991-2002

	P_0					
Year	***z*=50%**		***z*=60%**		***z*=70%**	
	P	**C**	**P**	**C**	**P**	**C**
1991	12.09	16.60	20.51	25.57	27.77	32.27
1992	11.39	16.83	19.42	26.38	28.33	36.17
1993	11.96	17.09	20.26	27.44	28.64	36.87
1994	10.74	14.44	18.96	25.30	26.88	33.51
1995	11.03	14.38	18.10	22.17	26.18	31.03
1996	11.22	15.78	18.70	23.89	28.09	34.69
1997	11.79	15.53	19.77	25.86	27.93	34.81
1998	11.72	16.24	19.60	25.79	27.67	35.08
1999	11.87	15.86	18.90	24.35	26.71	32.92
2000	12.04	14.82	19.97	24.39	27.67	33.17
2001	9.53	10.68	16.93	21.54	25.90	31.38
2002	9.83	10.53	16.78	20.20	25.18	30.03
% change 1991-2002	-18.69	-36.58	-18.16	-20.98	-9.32	-6.93

Source: Derived from the BHPS 1991-2002
P=population, C=children

Figure 4.7: Relative difference in P_0 (children: population)



Source: Derived from the BHPS 1991-2002
P=population, C=children

ii. The poverty gap ratio P_1

For all three poverty lines, the estimates of P_1 (as defined in Table 4.2) are higher for children than all individuals, suggesting that their incomes have persistently been further away from the poverty lines relative to the population as a whole (Table 4.5). In general, P_1 mirrored the evolution of the headcount index. Figure 4.8 shows that for all three poverty lines, there was a notable convergence in the indices for both samples. In 1991, the relative difference in P_1 between children and all individuals was highest at the 50 per cent threshold, however, by 2002, it reached the same for all thresholds.

Comparing P_0 and P_1, it is evident that although the greatest reduction in the headcount ratio occurred at the 50 per cent threshold (particularly for children), this was not matched by a comparable reduction in the poverty gap. Between 1991 and 2002, the headcount ratio fell by 19 per cent for the population and 37 per cent for children. The poverty gap declined by 5 per cent for the population and 18 per cent for children. In contrast, comparing the estimates for the 60 per cent and 70 per cent thresholds, the poverty gap indices declined proportionately more than the headcount for children. These patterns suggest that although a large proportion of children have been lifted out of poverty, it is those closer to the poverty line who have benefited the most. In contrast, proportionately fewer of the poorest children have seen a large enough improvement in their incomes to move them above the 50 per cent threshold.[20]

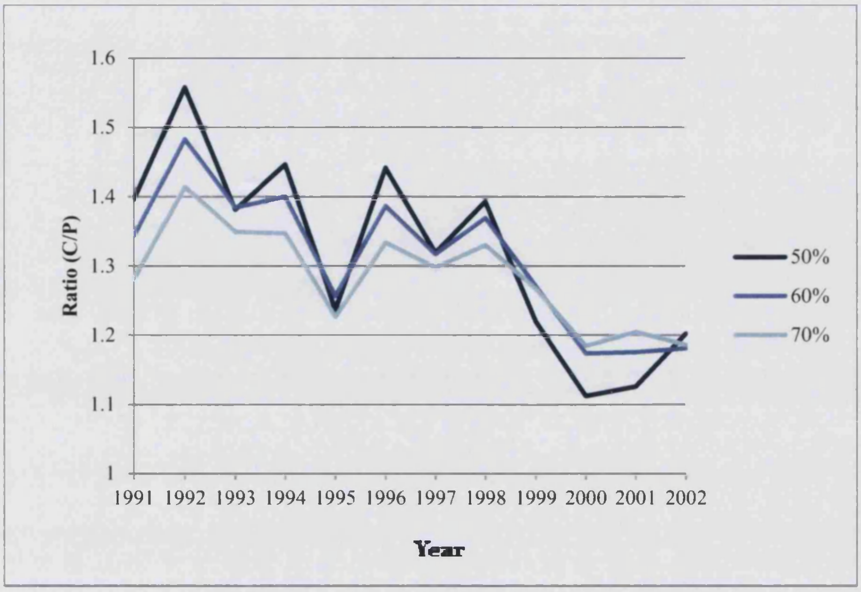
Table 4.5: Evolution of P_1, 1991-2002

	P_1					
Year	*z*=50%		*z*=60%		*z*=70%	
	P	**C**	**P**	**C**	**P**	**C**
1991	2.95	4.13	5.18	6.96	7.89	10.11
1992	2.94	4.58	4.99	7.40	7.71	10.90
1993	2.76	3.81	4.98	6.90	7.80	10.52
1994	2.72	3.94	4.72	6.61	7.31	9.85
1995	2.48	3.07	4.49	5.65	7.01	8.60
1996	2.75	3.97	4.79	6.65	7.47	9.97
1997	3.12	4.12	5.22	6.87	7.90	10.25
1998	2.90	4.04	5.04	6.90	7.71	10.26
1999	3.02	3.68	5.03	6.39	7.57	9.59
2000	3.30	3.67	5.41	6.35	8.03	9.51
2001	2.82	3.18	4.55	5.35	6.94	8.36
2002	2.80	3.36	4.51	5.33	6.88	8.16
% change 1991-2002	-5.29	-18.44	-12.96	-23.49	-12.84	-19.34

Source: Derived from the BHPS 1991-2002
P=population, C=children

[20] A caveat to these findings is that the lowest incomes are subject to measurement error, thus, the findings should be interpreted with caution.

Figure 4.8: Relative difference in P_1 (children: population)



Source: Derived from the BHPS 1991-2002
P=population, C=children

iii. The squared poverty gap ratio P_2

Finally, the squared poverty gap ratio (as defined in Table 4.2) is considered. Consistent with the P_0 and P_1 indices, P_2 was higher for children than for the population. Table 4.6 shows that there was a decline in P_2 between 1991 and 1995, which was steeper for children than the population. In contrast to the headcount and poverty gap indices, P_2 for all individuals appears to have increased for all three poverty lines after 1995. Over the entire period, there has been very little progress in reducing this index at the 50 per cent threshold (1.88 in 1991 compared to 1.77 in 2002).

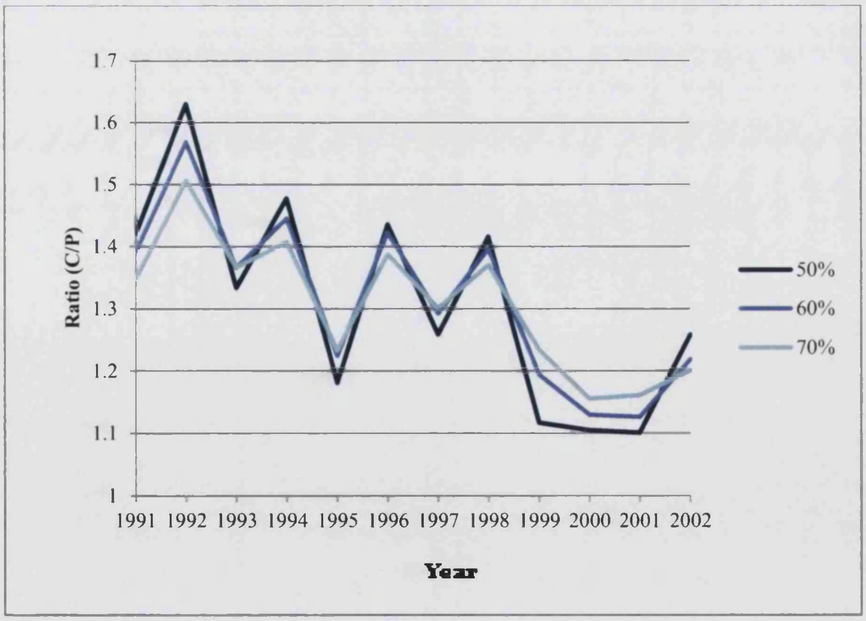
Although children experienced relatively greater declines in P_2 compared with all individuals, the proportional change was smaller than for the headcount and poverty gap indices (Figure 4.9). The smallest reduction occurred at the 50 per cent threshold (6 per cent compared to 19 per cent at z=70%). These findings imply that the reduction achieved overall child poverty has not been matched by a reduction in poverty for children near the very bottom of the income distribution.

Table 4.6: Evolution of P_2, 1991-2002

	P_2					
Year	*z*=50%		*z*=60%		*z*=70%	
	P	**C**	**P**	**C**	**P**	**C**
1991	1.33	1.88	2.16	3.00	3.32	4.48
1992	1.44	2.35	2.20	3.45	3.30	4.97
1993	1.15	1.53	1.97	2.69	3.15	4.30
1994	1.25	1.85	2.00	2.89	3.06	4.31
1995	1.09	1.29	1.82	2.22	2.86	3.52
1996	1.15	1.65	1.95	2.77	3.05	4.24
1997	1.38	1.74	2.23	2.88	3.37	4.39
1998	1.27	1.80	2.09	2.92	3.23	4.42
1999	1.38	1.54	2.18	2.60	3.27	4.04
2000	1.63	1.80	2.45	2.77	3.58	4.14
2001	1.47	1.62	2.14	2.41	3.09	3.59
2002	1.41	1.77	2.08	2.54	3.04	3.65
% change 1991-2002	+5.97	-6.11	-3.40	-15.39	-8.55	-18.51

Source: Derived from the BHPS 1991-2002
P=population, C=children

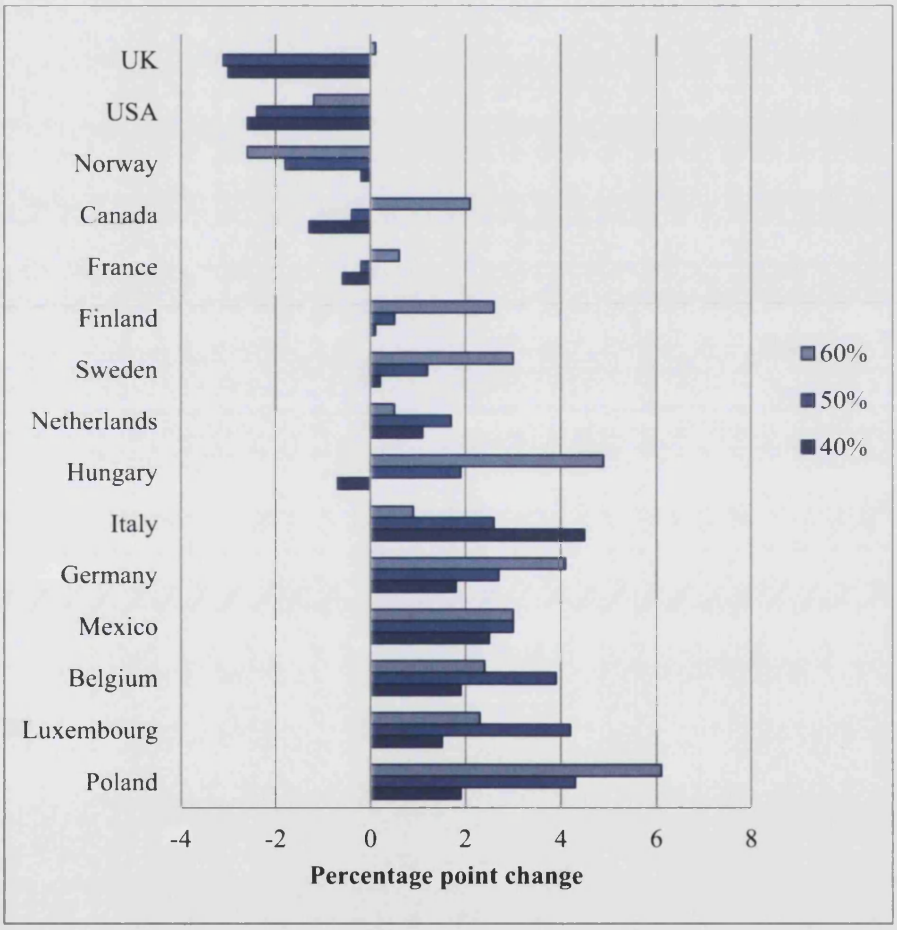
Figure 4.9: Relative difference in P_2 (children: population)



Source: Derived from the BHPS 1991-2002
P=population, C=children

With regards to cross-national reductions in child poverty, Figure 4.10 shows the rise and fall in child poverty rates according to the headcount measure for selected OECD countries using different poverty line specifications. Of the countries that reduced child poverty, the UK made the largest improvements followed by the USA and Norway (the latter from an already low level). The chart indicates that the largest reductions were made at the 40 per cent or 50 per cent of median income poverty lines (3 percentage points), whereas little change was made at the 60 per cent line, indicating that anti-poverty policies have benefited the poorest children the most.

Figure 4.10: Changes in child poverty rates in selected OECD countries during the 1990s



Source: Reproduced from Innocenti (2005), Figure 4, p.p. 12
Notes: The base year for changes in child poverty rates are measured from the years 1991 or 1992 except in the case of Belgium (1988) and Germany (1989). The latest dates refers to the following: 2001 (France, Germany), 2000 (Finland, Norway, Sweden, Luxembourg, Canada, Italy, USA), 1999 (Hungary, Netherlands, Poland, UK), 1998 (Mexico), 1997 (Belgium).

4.5.3 Poverty dominance

Section 4.3.1 highlighted that there is a lack of unanimity on the "best" poverty index for aggregating the extent of poverty. The analysis in Section 4.5.2 shows that whilst the three FGT poverty indices generally agree that child poverty has declined between 1991 and 2002, the quantitative change in poverty varies according to the poverty line cut-off and with the value of α. This section applies the method of stochastic dominance outlined in Section 4.3.2 to ascertain whether there was an unambiguous reduction in poverty across a range of poverty lines.

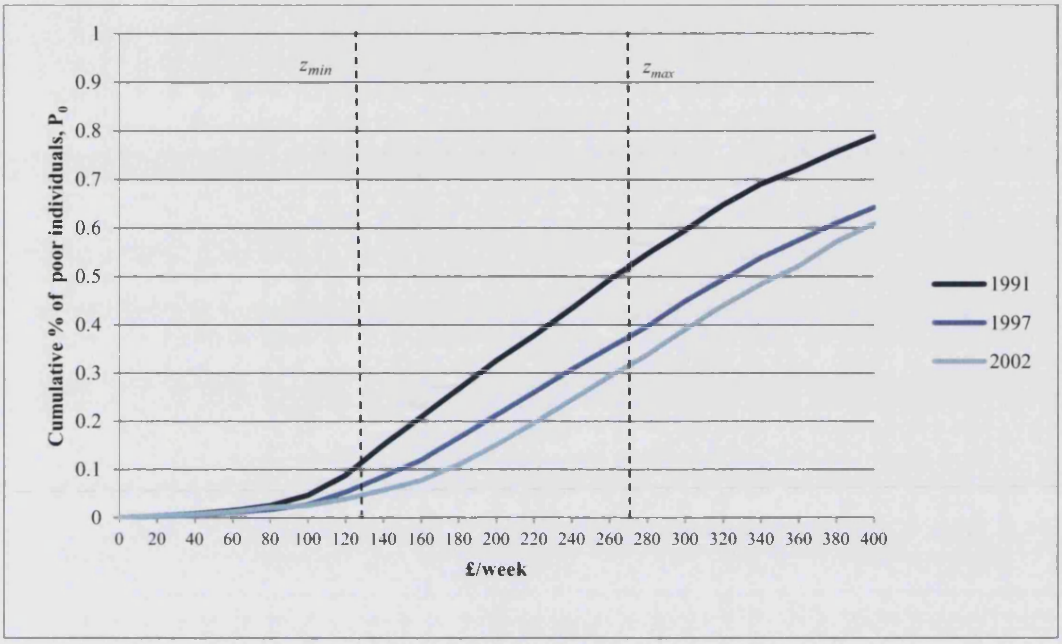
The interval of reasonable of poverty lines ($z \in [z_{\min} z_{\max}]$) is chosen to be 50% of the median income in 1991 as the lower bound (£131/week) and 70 per cent of the median income in 2002 (£268/week) as the upper bound. Cumulative distribution functions are constructed for the years 1991, 1997, and 2002, with the points along the curve corresponding to the headcount ratio at different income levels. The curves are initially inspected visually for dominance before applying the statistical tests using equation 4.11 to ascertain the robustness of improvements in poverty over the twelve year period.

Figure 4.11 displays the lower tail of the c.d.fs for the population and children. Since 1991, there has been a clear rightward shift in the c.d.fs, which implies that there has been a successive decline in the headcount ratio. The curves do not cross within the interval of poverty lines, therefore poverty rankings based on P_0, P_1 and P_2 are robust to the choice of poverty lines. Poverty in 2002 appears to be unambiguously lower than poverty in previous years.

To ascertain whether the rankings are statistically significant, t statistics using equation 4.11 are presented in Tables 4.7 and 4.8 to test the null hypothesis of non-dominance. 15 test points (i) are chosen within the interval of poverty lines (z). $\hat{P}_{year,i}$ corresponds to the proportion of individuals with incomes less than or equal to the i'th poverty line. Bishop et al. (1991) suggest that when testing for dominance at the ordinate level, if there is at least one positive (negative) significant difference and no significant differences of the opposite sign, dominance holds. The results confirm the visual inspection of the curves as all differences are statistically significant for the population and children. Thus, poverty decreased unambiguously between 1991 and 2002, and this finding is robust to all poverty lines within the chosen interval. As first-order dominance implies higher-order dominance, the findings suggest that the poverty gap (as measured by the area under the incidence curves) and the squared poverty gap (as measures by the area under the deficit curves) also declined. These findings are expected due to the growth incomes over the period, however, the dominance results are important as they enable robust statements to be made with regards to the change in poverty between 1991 and 2002.

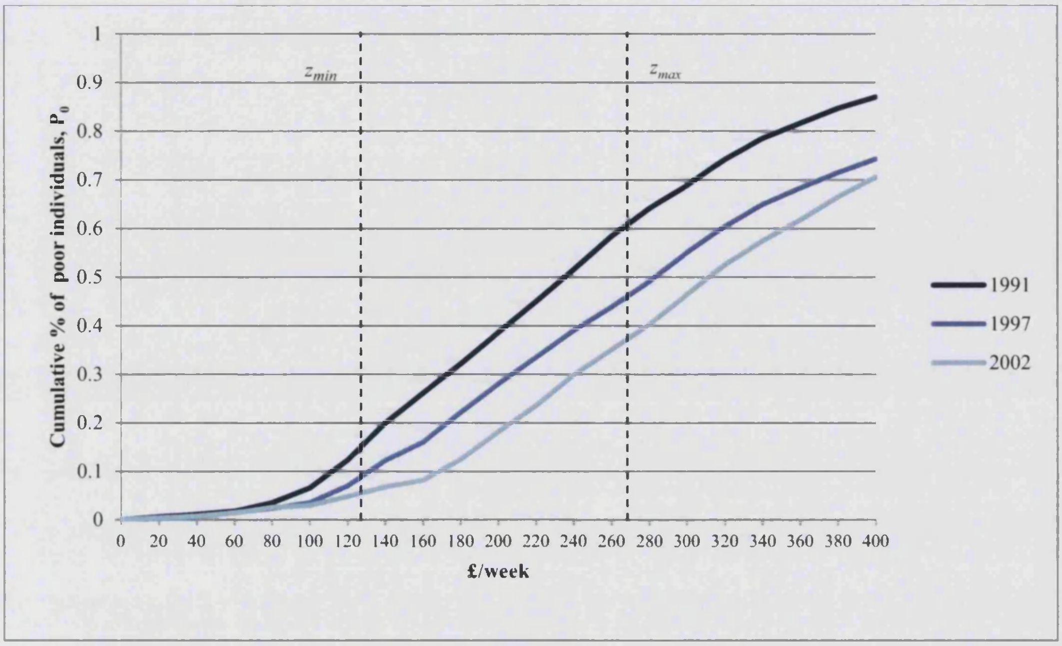
Figure 4.11: Poverty incidence curves with lower and upper bound poverty lines

Population



Source: Derived from the BHPS 1991-2002

Children



Source: Derived from the BHPS 1991-2002

Table 4.7: Tests for first-order stochastic dominance: population, 1991-2002

i	Poverty line (z) £/week	$\hat{P}_{1991,i}$	$\hat{P}_{1997,i}$	$\hat{P}_{2002,i}$	t_{91-97}	t_{97-02}	t_{91-02}
1	131	0.12	0.07	0.05	-6.18***	-4.17***	-10.41***
2	141	0.15	0.09	0.06	-7.72***	-4.52***	-12.25***
3	151	0.18	0.11	0.07	-8.5***	-5.06***	-12.83***
4	161	0.21	0.13	0.08	-8.86***	-5.77***	-14.32***
5	170	0.24	0.15	0.1	-9.16***	-5.84***	-14.66***
6	180	0.27	0.18	0.12	-8.92***	-6.54***	-15.18***
7	190	0.3	0.2	0.14	-8.56***	-6.83***	-15.54***
8	200	0.33	0.23	0.16	-8.79***	-6.2***	-15.09***
9	210	0.35	0.26	0.18	-8.22***	-6.52***	-15.02***
10	219	0.38	0.28	0.21	-8.35***	-5.94***	-14.42***
11	229	0.4	0.3	0.23	-8.32***	-5.63***	-14.31***
12	239	0.43	0.33	0.26	-8.49***	-5.59***	-14.38***
13	249	0.46	0.35	0.28	-8.86***	-5.3***	-14.21***
14	259	0.49	0.37	0.31	-9.22***	-5.29***	-14.67***
15	268	0.52	0.39	0.33	-9.61***	-4.87***	-14.72***

Table 4.8: Tests for first-order stochastic dominance: children, 1991-2002

i	Poverty line (z) £/week	$\hat{P}_{1991,i}$	$\hat{P}_{1997,i}$	$\hat{P}_{2002,i}$	$t_{91\text{-}97}$	$t_{97\text{-}02}$	$t_{91\text{-}02}$
1	131	0.17	0.1	0.06	-4.19***	-2.80***	-7.23***
2	141	0.2	0.12	0.07	-4.43***	-3.61***	-8.30***
3	151	0.23	0.14	0.07	-4.88***	-4.28***	-9.26***
4	161	0.26	0.17	0.08	-5.22***	-4.90***	-10.19***
5	170	0.29	0.2	0.11	-4.67***	-5.43***	-9.97***
6	180	0.32	0.23	0.13	-4.54***	-5.32***	-9.94***
7	190	0.35	0.27	0.16	-3.72***	-5.50***	-9.66***
8	200	0.38	0.3	0.19	-4.29***	-4.72***	-8.93***
9	210	0.41	0.33	0.22	-4.00***	-4.91***	-9.14***
10	219	0.44	0.35	0.25	-4.33***	-4.31***	-8.83***
11	229	0.48	0.37	0.28	-4.60***	-4.16***	-9.08***
12	239	0.51	0.4	0.3	-4.78***	-4.03***	-9.11***
13	249	0.54	0.42	0.33	-5.46***	-4.11***	-9.75***
14	259	0.57	0.45	0.36	-5.73***	-3.97***	-9.78***
15	268	0.6	0.47	0.39	-6.31***	-3.21**	-9.50***

Source: Derived from the BHPS 1991-2002
Note: *** Statistically significant at the 1% level; ** Statistically significant at the 5% level.

4.5.4 Profile of poverty

Section 4.5.2 investigated the aggregate changes in poverty between 1991 and 2002. The aim of this section is to analyse how the characteristics of poor children changed since the early 1990s. A useful feature of the Foster-Greer-Thorbecke class of indices is that they are decomposable, thus, the level of poverty can be computed for various sub-groups, j. Whilst sub-group analysis does not in itself elicit the causes of poverty, it draws attention to the close associations between poverty and wider inequalities in society, and indicates the need for specific policies to address poverty faced by various groups.

Tables 4.9 to 4.11 present a breakdown of the indices by each sub-group, $P_{\alpha j}$, for the years 1991, 1997, and 2002.

A consistent finding across all poverty lines is that worklessness is the largest risk factor associated with poverty. In 2002 and for z=60%, half of all children belonging to workless households were poor, which is six times the rate for children belonging to households where all adults are in paid work. Other important risk factors include the presence of 3 or more siblings (P_{0j} =30 per cent), living in social rented accommodation (35 per cent), and belonging to a lone parent (28 per cent).

As expected, a number of gradients within the sub-groups are evident. For example, the level of poverty is positively related with the number of children in the household and negatively related with the highest education level of the head. One-third of all children belonging to household heads with no qualifications were poor in 2002 compared with one-tenth of children belonging to heads with at least 'A'-Levels. Children belonging to lone parents were more likely to experience poverty (44 per cent) than children belonging to couples (13 per cent). Female and disabled heads also increased the risk of poverty, as did the presence of long-term sick people. The 'social-rented' group had higher levels of poverty than the 'private-rented' and 'owned' group. With regards to age of the head, the headcount index increased for the youngest heads (age 25 or less) between 1997 and 2002 at the 50 per cent and 60 per cent poverty line, however, it decreased for all other age categories. An explanation is that there was a growth in lone parents (who tend to have high worklessness rates) , particularly amongst the young, during this time period.

Whilst most groups of children experienced a reduction in poverty over the twelve year period, a notable finding is that children with particular 'adverse' characteristics experienced greater proportional declines. For example, between 1991 and 2002, poverty amongst lone parent children fell by 39 per cent compared with 28 per cent for couple children. Poverty for children in workless households fell by a fifth but increased by nearly a third for those in households where at least one adult worked but not all. These patterns are consistent across all poverty lines. Furthermore, the reduction in poverty for children with 3 or more siblings (33 per cent) was almost twice that for children with one sibling (18 per cent). This suggests that these groups have benefited from anti-poverty policies directed at them, as discussed in Chapter 1.

The trends in the poverty gap and squared poverty gap share a number of similarities with the headcount ratio. For example, worklessness and having three or more siblings are also the biggest risk factors that increase the poverty gap and severity indices. Thus, not only did these groups have the highest levels of poverty, they also had incomes that were further away from the poverty line, and there was a greater concentration of these children amongst the poorest of the poor. Furthermore, P_1 and P_2 exhibit the same sub-group gradients evident for the P_0.

There are also a number of differences across the indices. Where improvements over time are experienced for sub-groups across all three indices, reductions in the headcount index tend to be larger than reductions in the poverty gap index, which in turn, is larger than reductions in the squared poverty gap index. This suggests that is easier to reduce poverty by increasing the incomes of those near the poverty line than those with incomes much further below. For example, lone parent children experienced a 39 per cent fall in P_0, a 28 per cent fall in P_1, and a 5 per cent fall P_2 (z=60%). A similar pattern is evident for the female headed category. Only P_2 increased amongst children in households with at least one paid worker (but not all) and no workers, and with three or more siblings across all thresholds. In contrast to the headcount ratio, children belonging to heads with O/CSE level or no qualifications experienced an increase in the poverty gap and squared poverty gap index indices across all poverty lines.

It is interesting to note that children belonging to disabled heads tend to have lower levels poverty relative to all children according to the squared poverty gap index but higher levels according to the headcount index. This suggests that social assistance is helping these children to overcome "deep" poverty but is failing to lift their incomes above the poverty line.

With regards to comparisons of these findings with existing studies, Bradshaw (2006) compiled and compared the changes in the poverty rate for sub-groups of children based on the Family Resources Survey from the annual HBAI publications from 1999/2000 onwards. Whilst the time periods under consideration are not strictly comparable, they do overlap with the existing study. There are a number of findings in common. For example, Bradshaw found that between 1999/2000 and 2002/2003, the proportion of children living in households with income below 60 per cent of the median (before housing costs) had fallen for the lone parent, 3 or more children, workless, and social housing groups.

Table 4.9: Profile of poverty: headcount ratio P_0

	Poverty line	50%			60%			70%		
Variable	**Sub-group**	**1991**	**1997**	**2002**	**1991**	**1997**	**2002**	**1991**	**1997**	**2002**
Family type	Couple	8.59	9.00	5.84	14.56	12.77	10.43	20.69	19.32	18.07
	Lone	27.75	23.53	15.01	46.10	44.20	28.22	58.87	59.59	43.11
Sex of the head	Male	8.03	10.94	6.12	13.44	17.32	10.16	20.22	24.03	18.01
	Female	14.76	13.20	9.23	25.06	21.63	17.63	32.71	31.42	27.95
Highest qualification of head	'A'-Levels or higher	5.48	7.27	3.30	9.21	10.10	7.61	15.09	15.38	13.63
	O/CSE Level	11.72	16.25	10.05	20.31	25.28	19.83	28.34	36.34	31.76
	No qualifications	22.38	17.64	24.49	37.03	36.05	32.59	45.14	48.26	50.27
Number of adults in paid work	All adults in paid work	5.77	6.96	5.45	10.17	10.69	8.26	15.58	15.42	14.34
	At least 1 paid worker but not all	7.88	8.29	9.55	5.98	13.16	7.84	16.00	22.92	20.26
	No paid workers	41.71	33.00	27.31	63.09	55.24	50.56	75.33	74.66	70.72
Tenure	Owned	5.79	8.08	4.28	9.36	11.26	7.15	14.06	15.55	13.52
	Social rented	28.16	22.10	16.62	49.24	41.55	35.73	62.01	60.29	54.82
	Private rented	11.46	17.48	20.14	17.12	23.50	26.67	30.54	36.19	36.52
Age of head	<=25	16.15	11.66	23.58	37.48	19.96	30.37	55.59	44.18	37.04
	26-34	17.26	19.08	6.26	28.48	29.51	13.34	36.15	40.66	26.71
	35-44	8.62	9.79	8.89	13.90	14.51	15.12	20.89	21.35	22.62
	45+	8.17	7.83	5.19	14.62	18.37	11.65	18.86	24.19	20.95
Disability status of head	Not-disabled	11.95	12.34	7.53	2.21	19.80	13.92	27.14	28.24	23.50
	Disabled	9.03	10.96	14.15	38.12	23.65	22.73	66.31	36.46	25.75
Number of siblings	0	7.18	5.94	4.72	11.97	12.24	7.87	18.78	19.82	14.11
	1	8.34	7.45	7.57	16.37	14.56	13.43	22.69	21.04	19.82
	2	14.96	21.49	8.62	24.19	28.64	18.16	32.85	39.83	33.72
	3+	31.25	31.69	18.39	45.14	47.47	30.10	54.78	62.13	47.92
Number of long-term sick	0	11.64	7.10	7.91	19.73	11.70	13.91	26.69	24.33	23.56
	At least 1	23.61	13.19	7.62	37.82	21.32	17.33	57.87	29.18	23.91
All		16.6	15.53	10.53	25.57	25.86	20.20	32.27	34.81	30.03
N		2849	2425	2184	2849	2425	2184	2849	2425	2184

Source: Author's calculations based on the BHPS 1991-2002

Table 4.10: Profile of poverty: poverty gap index P_1

	Poverty line	50%			60%			70%		
Variable	**Sub-group**	**1991**	**1997**	**2002**	**1991**	**1997**	**2002**	**1991**	**1997**	**2002**
Family type	Couple	2.74	2.24	2.39	4.19	3.65	3.32	6.15	5.40	4.88
	Lone	4.65	5.29	4.56	10.14	9.66	7.33	16.20	15.85	11.46
Sex of the head	Male	2.60	2.37	2.45	4.01	4.27	3.33	5.81	6.60	4.83
	Female	3.32	3.30	3.20	6.05	5.51	4.89	9.39	8.55	7.50
Highest qualification of head	'A'-Levels or higher	2.34	2.18	1.59	3.18	3.20	2.22	4.47	4.53	3.38
	O/CSE Level	2.68	2.90	3.48	4.90	5.83	5.32	7.71	9.47	8.28
	No qualifications	4.69	5.22	7.56	8.87	8.43	10.98	13.53	13.30	15.56
Number of adults in paid work	All adults in paid work	1.98	2.30	2.01	3.02	3.36	2.81	4.53	4.69	4.01
	At least 1 paid worker but not all	2.38	3.35	3.35	5.69	2.74	4.25	6.52	8.89	9.50
	No paid workers	9.07	6.50	10.11	16.36	12.42	14.87	23.86	20.23	21.64
Tenure	Owned	2.04	2.31	1.93	2.93	3.52	2.52	4.22	4.91	3.60
	Social rented	5.58	4.04	5.45	11.22	8.26	8.90	17.60	14.52	14.29
	Private rented	2.96	5.19	5.19	4.72	7.88	8.09	7.50	10.90	11.48
Age of head	<=25	2.31	2.78	2.52	6.35	4.81	5.32	11.82	9.09	10.21
	26-34	3.75	3.60	1.75	6.99	6.89	3.17	10.69	10.90	5.77
	35-44	2.49	2.68	3.13	3.97	4.13	4.52	5.92	6.13	6.54
	45+	3.05	2.52	2.45	4.30	4.30	3.41	6.07	6.72	5.20
Disability status of head	Not-disabled	3.03	2.96	2.81	5.19	5.05	4.09	7.84	7.77	6.19
	Disabled	1.72	1.97	4.05	5.94	3.84	6.41	13.15	7.94	9.02
Number of siblings	0	2.04	1.76	1.85	3.30	2.85	2.62	4.98	4.76	3.74
	1	2.56	1.60	2.35	4.16	3.07	3.71	6.46	5.22	5.53
	2	3.13	5.07	2.93	5.99	8.45	4.58	9.18	12.04	7.69
	3+	6.80	7.78	10.28	11.97	12.41	12.17	17.36	18.55	16.47
Number of long-term sick	0	3.00	1.52	2.80	5.13	2.77	4.14	7.75	5.15	6.25
	At least 1	3.32	3.17	3.32	7.61	5.40	4.68	13.05	8.22	6.88
All		4.13	4.12	3.36	6.96	6.87	5.33	10.11	10.25	8.16
N		2849	2425	2184	2849	2425	2184	2849	2425	2184

Source: Author's calculations based on the BHPS 1991-2002

Table 4.11: Profile of poverty: squared poverty gap index P_2

	Poverty line	50%			60%			70%		
Variable	**Sub-group**	**1991**	**1997**	**2002**	**1991**	**1997**	**2002**	**1991**	**1997**	**2002**
Family type	Couple	1.48	0.88	2.39	2.07	1.52	1.79	2.89	2.31	2.39
	Lone	1.81	2.41	2.22	3.50	3.92	3.32	6.09	6.27	4.92
Sex of the head	Male	1.50	0.77	1.29	2.05	1.55	1.77	2.80	2.58	2.38
	Female	1.49	1.54	1.72	2.45	2.41	2.41	3.86	3.63	3.40
Highest qualification of head	'A'-Levels or higher	1.66	1.08	1.01	1.99	1.57	1.27	2.47	2.18	1.67
	O/CSE Level	1.17	1.01	1.79	1.96	2.04	2.57	3.11	3.52	3.68
	No qualifications	1.84	2.22	3.38	3.33	3.60	5.19	5.44	5.53	7.32
Number of adults in paid work	All adults in paid work	1.16	1.08	1.09	1.56	1.62	1.49	2.14	2.25	2.00
	At least 1 paid worker but not all	1.95	2.05	2.29	3.32	3.69	4.21	5.38	5.86	6.21
	No paid workers	3.98	2.58	5.33	6.65	4.67	7.47	10.25	7.77	10.32
Tenure	Owned	1.18	1.11	1.20	1.58	1.66	1.50	2.10	2.34	1.91
	Social rented	2.36	1.27	2.57	4.18	2.74	3.93	6.92	5.03	5.96
	Private rented	1.33	2.47	1.94	2.09	3.74	3.38	3.13	5.24	5.08
Age of head	<=25	0.79	1.43	1.75	1.82	2.14	2.35	3.75	3.37	3.52
	26-34	1.81	1.15	0.77	2.89	2.40	1.27	4.48	4.13	2.10
	35-44	1.22	1.29	1.67	1.83	1.94	2.31	2.65	2.78	3.16
	45+	1.78	1.16	1.50	2.35	1.82	1.92	3.11	2.80	2.54
Disability status of head	Not-disabled	1.51	1.25	1.55	2.29	2.09	2.11	3.41	3.23	2.91
	Disabled	0.33	0.51	1.21	1.30	1.22	2.45	3.44	2.45	3.86
Number of siblings	0	1.09	0.89	0.98	1.57	1.31	1.36	2.24	1.96	1.83
	1	1.40	0.67	1.24	1.98	1.17	1.78	2.86	1.96	2.53
	2	1.58	2.18	1.49	2.48	3.60	2.15	3.84	5.36	3.19
	3+	2.58	2.73	5.85	4.66	5.01	7.47	7.34	7.79	9.27
Number of long-term sick	0	1.52	0.47	1.44	2.29	0.98	2.05	3.39	1.74	2.87
	At least 1	0.70	1.36	2.10	2.16	2.25	2.66	4.32	3.46	3.49
All		1.88	1.74	1.77	3	2.88	2.54	4.48	4.39	3.65
N		2849	2425	2184	2849	2425	2184	2849	2425	2184

Source: Author's calculations based on the BHPS 1991-2002

4.6 Conclusion

This section has analysed cross-sectional trends in poverty based on the Foster-Greer-Thorbecke class of indices. The strength of the findings is that they go beyond simply looking at headcounts by considering income shortfalls from the poverty line and the breakdown of poverty for various sub-groups of children. Although the official HBAI publications provide annual disaggregated headcount statistics for various characteristics, they do not provide any measure of the "depth" or "severity" of poverty nor a temporal perspective on how the risk of poverty has changed over time.

A consistent finding is that children persistently experienced higher poverty levels, had incomes that were further away from the poverty lines, and were concentrated in the lowest part of the income distribution. In general, the proportional reduction in the headcount index has been greater than for the poverty gap, which in turn was greater than that for the squared poverty gap index. Children benefited from greater improvements in the indices than the population. Furthermore, progress has been made in reducing the differential between the population and child indices over time, and the greatest convergence occurred at the 50 per cent of median income poverty line, which reflects the increase in incomes of the poorest children, particularly after 1997. With regards to the profile of poverty, worklessness was consistently the largest risk factor across time for all three indices. Many of the gradients by sub-group were expected, however, the findings highlighted that a number of groups with adverse characteristics improved their position over time.

The poverty comparisons were sensitive to the choice of poverty lines and poverty measures. In order to check for the robustness of the results, this chapter advanced the analysis of poverty in Britain by applying stochastic dominance techniques. An advantage of this methodology is that it overcomes the arbitrariness associated with using very specific poverty lines. The tools of stochastic dominance confirmed that there was an unambiguous and statistically significant reduction in poverty between 1991 and 2002 for the population and children for a wide range of reasonable poverty lines.

In summary, the findings suggest that it has been relatively easy to increase the incomes of children closest to the poverty line, however, slower improvement has been made in tackling the "depth" and "severity" of poverty. This has important implications for the government's child poverty targets as different policies may be required to help children with incomes further away from the poverty line. The next chapter addresses some of the limitations of cross-sectional poverty measures by considering poverty longitudinally as short-term transitions.

Chapter 5 Assessing the 'True' Rates of Poverty Transitions in the Presence of Measurement Error

5.1 Introduction

Cross-sectional poverty rates are useful for gauging the level of poverty in a country during a particular time period. However, they are unable to provide important information about the extent of transitions into and out of poverty. Poverty rates may also understate the extent of poverty if individuals do not remain in the same state in successive years. This chapter complements and extends the research from Chapter 4 on the distribution of poverty by examining more closely the dynamics of poverty. It does this by exploiting the longitudinal nature of the BHPS to gauge the extent of short-term poverty mobility, and by drawing upon literature that has established that the presence of measurement error in income data results in biased estimates of transition rates. The specific aims of this chapter are, firstly, to apply latent Markov modelling techniques to poverty transition data by correcting for measurement error. Secondly, it establishes whether the process of poverty dynamics is different for children compared to the population. Thirdly, it compares trajectories of observed and error-corrected transitions in order to gauge the 'true' rates of poverty mobility and persistence.

This chapter is organised as follows. Section 5.2 surveys the literature on methodological developments in the measurement of poverty mobility. This is followed, in Section 5.3, by a descriptive analysis of observed poverty mobility. Sections 5.4 and 5.5 provide an overview of latent Markov chain modelling and assessment of model fit techniques. 5.6 sets out the research hypotheses. The empirical results are presented in Section 5.7 in two ways. Firstly, the fit statistics for the models are compared, and secondly the trends in transition probabilities are presented, which compare observed and error-corrected probabilities. Finally, Section 5.8 concludes with a summary of the findings and a discussion of the limitations of the techniques used in this chapter.

5.2 Previous literature

5.2.1 Traditional measures of poverty mobility

Poverty mobility is defined as the changes in income that give rise to movements into and out of poverty among the same individuals over time or between generations (Fields and Ok, 1999). A widely used descriptive technique for analysing mobility is through transition (or turnover) tables, which cross-tabulate states of a particular phenomenon at two time points. Probabilities in the main diagonal of the matrices denote the proportion of individuals who do not leave their original poverty status, and off-diagonal probabilities represent the proportion of individuals who change poverty status. If the diagonal elements are closer to one, this implies a greater level of immobility between time periods.

There are three limitations with poverty dynamics research that use transition tables. Firstly, they tend to focus on transitions between the first and last periods or arbitrary intervals, even where longitudinal data are available. This is not only wasteful of valuable data but also ignores the trends in poverty mobility over time. Secondly, it assumes that the population is homogenous and that mobility rates can be averaged across the population sample. This assumption ignores the possibility of heterogeneity in mobility patterns. Finally, income data are susceptible to measurement error, sources of which include (Moore et al., 2000; Micklwright and Schnepf, 2007):

i. deliberate underreporting;
ii. misreporting the sources of income (for example, wages, social assistance, and assets) and the amounts pertaining to these sources;
iii. recall error due to the length of the retrospective period or a lack of records;
iv. idiosyncratic understanding of income may cause individuals to misreport, for example, not declaring small or irregular amounts from occasional work;
v. Using a single survey question to cover all sources of income;
vi. Banding of income data in surveys, which leads to loss of information on the variation of income within each band;
vii. Interviewing only one adult per household about total household income regardless of the number of adults in the household.

The main implication of measurement error is that fluctuations in measured income that are caused by measurement error are mistakenly attributed to actual income fluctuations (Skinner, 2000). Thus, observed transitions result from a combination of true mobility and spurious change resulting from measurement error (Van de Pol and De Leeuw, 1986; Hagenaars, 2002). A possible effect is that poverty exits and entries are overstated, whilst persistence is understated.

In order to derive more accurate estimates of poverty mobility, it is necessary to employ methods that take these shortcomings into account.

5.2.2 Correcting for measurement error in poverty dynamics

Skinner and Torelli (1993) and Skinner (2000) discuss two main approaches to adjusting for measurement error in transition tables for discrete variables. In the first approach, explicit use is made of auxiliary data, which is reconciled against survey data through a misclassification matrix. Auxiliary data can be derived from validation or administrative records, and is assumed to provide a better approximation of the true values than the original survey data. If the auxiliary and survey sources elicit the same sequence with regards to the transition phenomena under study, then evidence is provided for the nature of true change between time points. However, any mismatch between the two sources is posited to be a direct estimate of measurement error.

Validation data can be obtained through re-interviewing a sub-sample of the same individuals, however, this is costly and the samples may not be fully representative. These limitations can be overcome through the use of administrative data (for example, government benefit data), which are compared against survey values. In their study of methods for linking these two data sources, Jenkins et al. (2004) acknowledge the associated merits and current limitations: "*In general, record linkage has several attractions for household survey producers and users: it may help diminish respondent burden, additional information may be collected, and measurement error may be reduced. Whether this potential can be fully realised is not yet known, as linkage with household surveys is in its infancy, not only in Britain but also in many other countries*" (p.1). Other limitations include the self-selection bias inherent in administrative records and difficulties in obtaining the data due to confidentiality issues.

The extent to which household surveys overstate mobility compared with data from administrative registers has been directly examined by Basic and Rendtel (2004). They compare five waves of European Community Household Panel (ECHP) data for Finland with administrative data over the same period (1995-1999). Their results show that much of the observed movement into and out of poverty in the survey data reflects measurement error, and that this has a much greater impact than attrition bias in the longitudinal survey.

Jenkins (2000) and Devicienti (2000) use ad hoc adjustments by defining genuine poverty transitions as occurring only if post-transition income is greater (less) than 110 per cent (90 per cent) of the poverty line. A weakness of this approach is that the thresholds are arbitrary and it unclear whether it captures 'genuine' poverty transitions only. Gottschalk and Danziger (2001) and Hill and Jenkins (2001) smooth out transitory variations in income by averaging out individual longitudinal incomes to derive "permanent income" levels. In averaging out the transitory component of income, important systematic patterns of change may be masked as such an approach does not differentiate between individuals who stay in or out of poverty throughout the measurement period, and those who transition to a different state.

Methodological developments for error correction in repeated categorical indicators have occurred in the fields of latent Markov chain analysis. These models assume that observed response patterns are derived from either a single, or from a mixture of Markov chains in the population. These chains may be subject to measurement error, and thus considered to be latent phenomena, imperfectly represented by the indicator variables (Poulsen, 1982; Langeheine and van de Pol, 1990, 1994, 2002).

The earliest study on error-corrected poverty dynamics was conducted by Rendtel, Langeheine and Bernsten (1998) using three waves (1985-1986) of the German Socio-Economic Panel (GSOEP). The authors compared estimates from two measures of income based on the head's self assessment of total household income and computed household income from aggregating the incomes of each household member. Using a single chain Latent Markov specification, they estimated that almost half of the observed poverty mobility in the data could be accounted for by measurement error.

Moisio (2004) and Breen and Moisio (2004) draw upon the modeling framework of Langehiene and van de Pol (1990,1994, 2002) to correct for measurement error in poverty dynamics for ten EU countries using four waves (1994-1997) of the ECHP. The three main findings were that a latent mover-stayer Markov model gives an acceptable fit to all ten transition tables, that poverty mobility is over-estimated by between 25 and 50 percent if measurement error is ignored, and that once error is accounted for, poverty rates show less cross-national variation.

Whelan and Maitre (2006) replicate Breen and Moisio's methodology using 5 waves (1994-1998) of the ECHP for nine EU countries but also include indicators of deprivation[21] in order to investigate whether the findings of previous research on the lack of overlap between income poverty and deprivation[22] is attributable to measurement error. The authors find similar patterns for both indicators: the levels of poverty and deprivation mobility are lower at the latent than observed level. Finally, taking measurement

[21] Deprivation was measured according to a weighted index of items pertaining to the possession of particular household goods, affordability, and arrears.

[22] See, for example, Whelan et al. (2001, 2003, 2004).

error into account appears more likely to exacerbate rather than diminish the lack of overlap between income and deprivation indicators that was highlighted in previous research.

In summary, latent Markov chain analysis makes it possible to separate true mobility from spurious change arising from measurement error by making assumptions about the structure of measurement error and the nature of the underlying stochastic process. A consistent finding from studies employing this method is that firstly, the presence measurement error is significant in poverty mobility data. Secondly, observed transition probabilities exaggerate the magnitude of poverty mobility and under-state poverty persistence compared to latent transition probabilities. These findings are robust across the number of panel waves used, the country under study, and the specification of the poverty indicator.

This chapter extends the literature on poverty dynamics by using latent Markov chain modelling to assess the impact of measurement error on observed poverty transitions.

5.3 Descriptive analysis of observed poverty transitions

Before proceeding to model poverty mobility, this section provides some stylised facts about the nature of poverty dynamics through a descriptive analysis of i) the length of time spent in poverty, ii) the risk of poverty reocurrence, and iii) transitions to different income groups. This analysis will provide a context and justification for the modelling techniques describe in Section 5.4.

i. The length of time spent in poverty

The analysis sub-samples consist of those individuals who were present in all twelve waves. This consisted of 4,441 individuals of which 519 were children. The relatively small sample size for the latter is because some were born after 1991 (thus, entered the panel after the first wave), became adults, or left the sample. [23]

Table 5.1 shows the percentage of all individuals and children classified as poor *t* times out of twelve years (not necessarily continuously so).

The estimates show that the majority of both groups never experience poverty, but this likelihood is lower for children (50 per cent) than all individuals (60 per cent). The likelihood of experiencing poverty more than once decreases as the observation period increases. Thus, approximately 1 per cent of both samples

[23] The balanced sample is chosen because the software used for modeling poverty transitions using Markov models requires non-missing data.

report being poor at all twelve waves. The risk of experiencing poverty on one or more occasions is approximately twice the poverty rate. This is because of a substantial amount of mobility - half of all children were touched by poverty at least once, which is approximately one-fifth higher than for all individuals (39.5 per cent). Whilst the risk of experiencing poverty in all twelve years is rare, 6 per cent of children were touched by it in eight or more years. Thus, children are observed to be as likely as the population to be always poor but less likely to be always non-poor. Furthermore, there is greater poverty mobility amongst children.

Table 5.1: Proportion of individuals classified as poor *t* years out of twelve (1991-2002)

	% poor in *t* years	
t years	All individuals	Children
0	60.11	49.56
1	12.13	13.22
2	7.25	10.49
3	4.17	6.21
4	3.16	4.87
5	3.31	4.12
6	2.12	3.31
7	1.73	2.21
8	1.42	1.5
9	1.15	1.25
10	1.05	1.09
11	1.03	1.09
12	0.95	0.92
Total	100	100
Average cross-sectional poverty rate (%)	18.99	24.41

Source: Derived from the BHPS 1991-2002.
Note : balanced sample of all individuals and children.
Poverty line=60 per cent median contemporary income

ii. Poverty reoccurrence

Table 5.2 shows the risk of poverty reoccurring in later waves conditional upon being poor in wave one. The experience of poverty in wave 1 is associated with an increased risk of poverty in subsequent years. Furthermore, this risk does not appear to fall sharply in subsequent waves. Thus, in wave two the conditional probability was 0.6 for children and by the tenth wave it was still as high as 0.54. These patterns confirm the findings of Whelan and Maitre (2006) and Breen and Moisio (2004).

Table 5.2: Risk of poverty in subsequent waves conditional upon being poor at t=1

Probability of poverty reoccurrence	Population	Children
$\Pr(Poor_{t=2} \mid Poor_{t=1})$	0.57	0.60
$\Pr(Poor_{t=3} \mid Poor_{t=1})$	0.47	0.52
$\Pr(Poor_{t=4} \mid Poor_{t=1})$	0.44	0.47
$\Pr(Poor_{t=5} \mid Poor_{t=1})$	0.45	0.47
$\Pr(Poor_{t=6} \mid Poor_{t=1})$	0.40	0.38
$\Pr(Poor_{t=7} \mid Poor_{t=1})$	0.48	0.52
$\Pr(Poor_{t=8} \mid Poor_{t=1})$	0.44	0.52
$\Pr(Poor_{t=9} \mid Poor_{t=1})$	0.44	0.44
$\Pr(Poor_{t=10} \mid Poor_{t=1})$	0.45	0.54
$\Pr(Poor_{t=11} \mid Poor_{t=1})$	0.37	0.40
$\Pr(Poor_{t=12} \mid Poor_{t=1})$	0.39	0.40

Source: Derived from the BHPS 1991-2002.
Note : balanced sample of all individuals and children
Poverty line=60 per cent median contemporary income
t=1 is wave 1 (1991) of the BHPS

iii. Transitions to different income groups

Finally, transitions within the context of the income distribution are considered. This analysis is useful as it provides an insight into the extent of income changes around the poverty line. If most of the movements are close to the poverty line, it may reflect "noise" from measurement error or temporary income volatility, which may not always translate into real changes in living standards.

Table 5.3 presents a transition matrix for children which shows the average annual outflow probabilities between 13 income groups over the 1991-2002 period. The income groups are defined by various proportions of median income. Thus, the top group had an income greater than 160 percent of the median, and the lowest group had an income less than 10 per cent of median income. The bottom left panel of the table represents entries into poverty (those who move from above the 60 per cent median income threshold to below it). The top right panel represents exits from poverty (those who move from below the 60 per cent median income threshold to above it). The remainder panels show the proportions of individuals who remained within poor or non-poor income categories. The diagonal represents the proportion of individuals who did not change income groups, with smaller values indicating greater mobility over time.

The top left panel shows that children were, on the whole, more likely to remain below the poverty line than to exit poverty. Similarly, those with incomes above the poverty line were more likely to remain non-poor than to enter poverty.

The probabilities on the diagonal of Table 5.3 tend be highest at the tails of the income distribution, which means higher persistence in and lower outflow from the highest and lowest income groups. With the exception of the richest two groups, on average, less than 40 per cent of children in any one group remained in the same category from one year to the next. There is greater mobility at the lower end of the income distribution. One third of the poorest children (">0, <=10") remained in the same category, in contrast to two-thirds of the richest children (">160"). However, it also important to note that of those children in poverty, the poorest (">0, <=10") were the most immobile, which suggests that social assistance programs were not reaching the poorest of the poor. This finding supports the pattern of change in the FGT indices in Chapter 4, i.e., the reduction in the headcount index was greater than the reduction in the poverty gap index, which in turn was greater than the reduction in the squared poverty gap index.

Children who were further away from the poverty line at t were less likely to exit or enter poverty. For example, 28 per cent of children with incomes that were at most 10 per cent of the median left poverty the following year compared with 42 per cent with incomes just below the poverty line (">50, <=60"). Of the latter, half (20 per cent) moved just above the poverty line and a quarter (9 per cent) moved up by two categories. The same pattern is reflected amongst those who fell into poverty: those with incomes just above the poverty line at $t+1$ were almost ten times more likely to enter poverty (29 per cent) the following year than those with the highest incomes (4 per cent). Of the entrants with incomes just above the poverty line in the previous year, 60 per cent moved down by one income category and 30 per cent moved down by two categories.

In general, a similar pattern and magnitude of mobility is evident for all individuals (appendix Table A5.1). There are, however, a few notable relative differences. At each income group, children were less likely than all individuals to exit poverty and slightly more likely to enter poverty. The poorest children were less likely to exit poverty (28 per cent) compared with all individuals (37 per cent), however, the estimates for both samples converged at just below the poverty line (42-44 per cent).

Table 5.3: Outflow rates (%) from wave *t* income group origins to wave t+1 income groups destinations: children, 1991-2002

% of median income at *t*	% of median income at *t+1*: >0, <=10	>10, <=20	>20, <=30	>30, <=40	>40, <=50	>50, <=60	>60, <=70	>70, <=80	>80, <=90	>90, <=100	>100, <=120	>120, <=160	>160	Total
>0, <=10	**33.3**	13.0	0.0	7.4	16.7	1.9	7.4	1.9	0.0	1.9	7.4	3.7	5.6	100
>10, <=20	14.3	**10.7**	3.6	21.4	14.3	17.9	7.1	3.6	3.6	0.0	0.0	3.6	0.0	100
>20, <=30	6.1	1.5	**6.1**	18.2	18.2	13.6	9.1	9.1	6.1	3.0	7.6	1.5	0.0	100
>30, <=40	1.9	1.9	7.0	**18.8**	22.1	14.1	9.4	3.8	6.1	2.8	5.6	3.3	3.3	100
>40, <=50	0.2	1.2	2.8	13.0	**31.4**	21.0	12.0	6.6	4.7	1.7	1.2	3.1	1.2	100
>50, <=60	0.6	1.4	1.8	8.6	16.0	**29.5**	20.0	9.0	5.6	1.2	3.4	1.4	1.4	100
>60, <=70	0.9	0.2	0.7	1.4	8.8	17.2	**28.0**	14.8	16.0	4.9	4.2	1.5	1.5	100
>70, <=80	0.0	0.0	1.0	2.3	5.5	8.3	18.6	**27.3**	16.1	9.3	7.2	2.5	2.1	100
>80, <=90	0.0	0.2	0.6	2.2	1.8	6.7	12.6	17.0	**22.9**	16.4	14.6	3.6	1.4	100
>90, <=100	0.2	0.2	0.4	0.8	1.5	2.5	5.7	9.9	15.0	**31.1**	22.4	8.9	1.7	100
>100, <=120	0.3	0.3	0.0	1.5	1.3	2.3	3.0	5.4	6.4	16.9	**36.4**	22.4	3.9	100
>120, <=160	0.6	0.0	0.5	1.0	0.6	0.7	2.4	2.5	2.3	5.3	21.9	**50.8**	11.4	100
>160	0.2	0.2	0.4	0.8	0.9	1.5	0.8	1.5	0.8	3.4	5.8	21.0	**62.9**	100
All	0.86	0.59	1.1	3.93	7.24	9.05	10.51	9.47	9.16	9.67	14.23	14.86	9.32	100

Source: Derived from the BHPS 1991-2002
Note : balanced sample of children
Transition rates are average rates from pooled waves of BHPS data

In summary, the descriptive analysis shows that a number of underlying features are evident with regards to poverty mobility. Most individuals never experience poverty, however, children are less likely to be never poor compared with all individuals. The majority of those who do experience poverty tend to do so for a short duration. The proportion of individuals who experience poverty at least once is approximately twice the average cross-sectional poverty rate. This is because most people who are ever poor experience poverty for a year, but are likely to transition in and out of poverty more than once. Whilst long episodes of poverty exist, they are rare. There is much mobility across the income distribution, but most transitions are to adjacent income groups. A large proportion of individuals who have exited poverty or have fallen into it have incomes near the poverty line. In combination with the short episodes, this suggests that the presence of “noise” in the income data arising from transitory income fluctuations or measurement error is leading to an overstatement of poverty mobility. The aim of the next section is to derive a ‘truer’ picture of poverty mobility by correcting for measurement error.

5.4 Latent Markov chain modeling

The descriptive analysis has shown that being poor at a particular time in point is a good predictor of being poor in subsequent periods, thus, transitions can not be argued to be purely random or stationary. For repeated measures of categorical variables, Markov models are one approach for analysing short-term changes in poverty status from one time point to the next. Since the 1950's, the social science literature has explored whether the theory of Markov chain models could be applied to data on intergenerational social mobility (Prais, 1955; Bartholomew, 1973). This section is divided into three parts. i) introduces the Markov chain model; ii) addresses the limitations of the simple Markov model with a discussion of the Mover-Stayer Markov model; and iii) discusses the incorporation of measurement error in Markov models via the inclusion of latent variables.

i. Markov chain models

The first-order Markov chain assumes that the state occupied at t depends only on the state occupied at $t-1$. The probability of outcomes at $t+1$ are again determined by those at t, and so on. The dynamics of poverty across time are modeled by assuming a discrete time process in order to understand change, stability or both. They do not describe the process of change between time points in the way that continuous time models do.

As will be demonstrated, the observed Markov model is the basic building block for the hierarchy of more complex variants of Markov chain models.

Let X be an observed variable which describes the poverty status of an individual. X has $k=2$ categories (1=poor, 2= not-poor) and is measured at a total of 12 annually spaced time points. The measurements at every time point are denoted as:

$$x_t \qquad\qquad t=1,\dots,12 \qquad\qquad (1)$$

The basic Markov process can be expressed as:

$$p_{ij}(t) = \Pr(X_t = j \mid X_{t-1} = i) = \tau_{j|i}^{t,t-1} \qquad i=1,2; j=1,2 \qquad\qquad (2)$$

where $p_{ij}(t)$ denotes the conditional probability of moving to state j in the current period, given that state i was occupied in the previous period.

The dependencies between successive realisations of X can be presented in a kxk matrix of conditional transition probabilities, with each cell denoting the conditional probability for a certain occurrence at t given a certain occurrence at $t-1$. Let $\boldsymbol{P}$ be a kxk transition matrix with the elements of the rows of $\boldsymbol{P}$

always summing to one $(\sum_{j=1}^{k} p_{ij} = 1)$. Table 5.4 shows a basic 2x2 transition matrix for the change in poverty status between two time points and descriptions for each cell:

Table 5.4: Transition matrix of conditional probabilities between t and t-1

		t		
		j Poor	j Not-poor	
t-1	i Poor	"Short-term persistent poverty" $\tau^{t,t-1}_{poor \mid poor}$	"Poverty exit" $\tau^{t,t-1}_{not-poor \mid poor}$ =1- $\tau^{t,t-1}_{poor \mid poor}$	1
	i Not-poor	"Poverty entry" $\tau^{t,t-1}_{poor \mid not-poor}$	"Stay non-poor" $\tau^{t,t-1}_{not-poor \mid not-poor}$ = 1- $\tau^{t,t-1}_{poor \mid not-poor}$	1

$\tau^{t,t-1}_{poor|poor}$ gives the probability of being poor at two successive time periods ("short-term persistent poverty"). Analogously, $\tau^{t,t-1}_{not-poor|not-poor}$ gives the probability of remaining non-poor. As the row probabilities sum to 1, the transition probability matrix also provides the probabilities associated with moving from poverty at t-*1* to non-poverty at *t* "poverty exit" and from non-poverty to poverty "poverty entry".

Using the notation of Langeheine and van de Pol (2002), a Markov model with twelve repeated measures can be expressed as:

$$P_{x_{91}x_{92}..x_{02}} = \delta_{x_{91}} \tau_{x_{92}|x_{91}} \tau_{x_{93}|x_{92}} \ldots \tau_{x_{02}|x_{01}} \quad t=1,\ldots,12 \qquad (3)$$

$P_{x_{91}x_{92}..x_{02}}$ is the model-based proportion of respondents in the $x_{91}, x_{92}, \ldots, x_{02}$ cell of the twelve-way transition table.

$x_{91}, x_{92}, ..., x_{02}$ are the observed realisations of poverty status at *t=1,2,...,12* measured annually on a dichotomous scale, where 1=poor and 2=not-poor.

$\delta_{x_{91}}$ is the observed proportion of the sample who are poor or not-poor at *t=1* and corresponds to the initial marginal distribution of poverty status.

$\tau_{x_{92}|x_{91}}, \tau_{x_{93}|x_{92}}, ..., \tau_{x_{02}|x_{01}}$ are observed transition probabilities between consecutive time points. Specifically, $\tau_{x_{92}|x_{91}}$ represents the transition probability from *t=1* to *t=2* for those in category *j* given that they were in category *i* at *t=1*.

If the transition probabilities are constant over time, ($\tau_{x_{92}|x_{91}} = \tau_{x_{93}|x_{92}} =, ..., = \tau_{x_{02}|x_{01}}$), the Markov model is referred to as stationary. If they are allowed to vary over time, the Markov model is referred to as non-stationary.

Equation (3) assumes that the sample of observations arises from a homogeneous population that experiences the same pattern of transitions over time and often leads to a poor fit to the data. It is possible, however, that the population is comprised of an unobserved mixture of sub-populations, each with qualitatively different Markov chains (Langeheine and van de Pol, 1990, 1994, 2002). Not only can a single-chain Markov model lead to biased parameter estimates, it can also lead to incorrect conclusions regarding the nature of social processes over time. Poulsen (1982) presented a formulation for the introduction of population heterogeneity by increasing the number of chains in the simple Markov model. This is known as the mixed Markov model and is defined as:

$$P_{x_{91}x_{92}\ldots x_{02}} = \sum_{s=1}^{S} \pi_s \delta_{x_{91}|s} \tau_{s,x_{92}|x_{91}} \tau_{s,x_{93}|x_{92}} \ldots \tau_{s,x_{02}|x_{01}} \quad t=1,\ldots,12 \tag{4}$$

π_s represents the proportions of the sample in each of the *s* Markov chains *(s=1...S)*. $P_{x_{91}x_{92}\ldots x_{02}}$ is obtained by summing over all simple Markov chains. The remaining parameters are interpreted as in equation (3) except that they are conditional upon chain membership.

ii. The Mover-Stayer Model

Blumen, Kogan and McCarthy (1955) modified the Markov chain model by developing a variant known as the Mover-Stayer model. By using quarterly data from the Social Security Administration on major industrial groups for the study of social mobility, the authors found that the fit of a single Markov chain to their data was poor. They argued that initial attempts at modelling mobility dynamics using simple Markov chain models treated socially heterogeneous populations as being characterised by a homogeneous transition process for all individuals. In order to provide a more suitable description of mobility over time, they modified the basic Markov model by allowing individuals to have heterogeneous transition matrices by sub-dividing the population into an unobservable mixture of "mover" and "stayer" chains. "Movers" have positive probabilities of moving between one state and another, the evolution of which can be modelled by a first-order Markov chain. "Stayers", on the hand, remain with certainty in the same state *(i, j)* for all time periods ($\tau_{j|i} = 1$ if i=j) and have zero probability of moving to another state ($\tau_{j|i} = 0$ if $i \neq j$). As this model is a variant of the mixed Markov model with two chains, it can be expressed as equation (4), except that that the transition probabilities for the Mover chain are equal to an identity matrix.

The Mover-Stayer model is important and relevant to the study of longitudinal poverty as the descriptive findings showed that:

i. the majority of individuals never experienced poverty and only a minority stayed poor in all twelve years. The stayer chain would be appropriate for modelling this.

ii. Of those who experienced poverty did so for a short duration, however, the risk of poverty reoccurrence remained relatively high. This gave rise to considerable mobility (40 per cent of all individuals and 50 per cent of children) arising from poverty entries and exits. The mover chain would provide an appropriate description for this group of people.

Although the mixed Markov model posits that the population is heterogeneous with respect to the underlying stochastic process, it could still lead to a poor fit to the data as it assumes that the observed responses are free of measurement error. The next set of models separates the "true" values from the observed ones by combining Latent Class and Markov chain models.

iii. The Latent Mixed Markov Model

When data are subject to measurement error, observed transitions are the product of true mobility and spurious change resulting from measurement error. The latent Markov model makes it possible to separate both through defining a structural part, which describes the true dynamics among latent variables by means of Markov chains, and a measurement part, which relates each latent variable to its observed counterpart by a response matrix. This important contribution to the field of Markov chain analysis is attributable to Wiggins (1973), who addressed the problem of measurement error by postulating that manifest categorical responses are imperfect measures of true latent states, and consequently, obtained transition probabilities at the latent level. This was done by merging the latent class model with a single Markov chain model. A latent class is a category of a latent variable which is indirectly measured via observed categorical variables.

Langeheine and van de Pol (1990) introduced heterogeneity into the latent Markov model by allowing more than one Markov chain to have its own measurement part. This is known as the latent mixed Markov model and is expressed as:

$$P_{x_{91}x_{92}\cdots x_{02}} = \sum_{s=1}^{S} \sum_{a=1}^{A} \sum_{b=1}^{B} \cdots \sum_{l=1}^{L} \pi_s \delta_{a|s} \rho_{s,x_{91}|a} \tau_{s,b|a} \rho_{s,x_{92}|b} \tau_{s,c|b} \cdots \rho_{s,x_{02}|l} \tau_{s,k|l} \qquad (5)$$

The twelve latent variables are denoted $a=1,...,A$, $b=1,...,B$, etc.

π_s is the proportion of observations in Markov chain s=1,…,S. When $s=1$, equation (5) is the latent analogue of the simple observed Markov model (equation (3)).

$\delta_{a|s}$ is the probability that a respondent belongs to one of A true latent classes at t=1 conditional upon membership in Markov chain s.

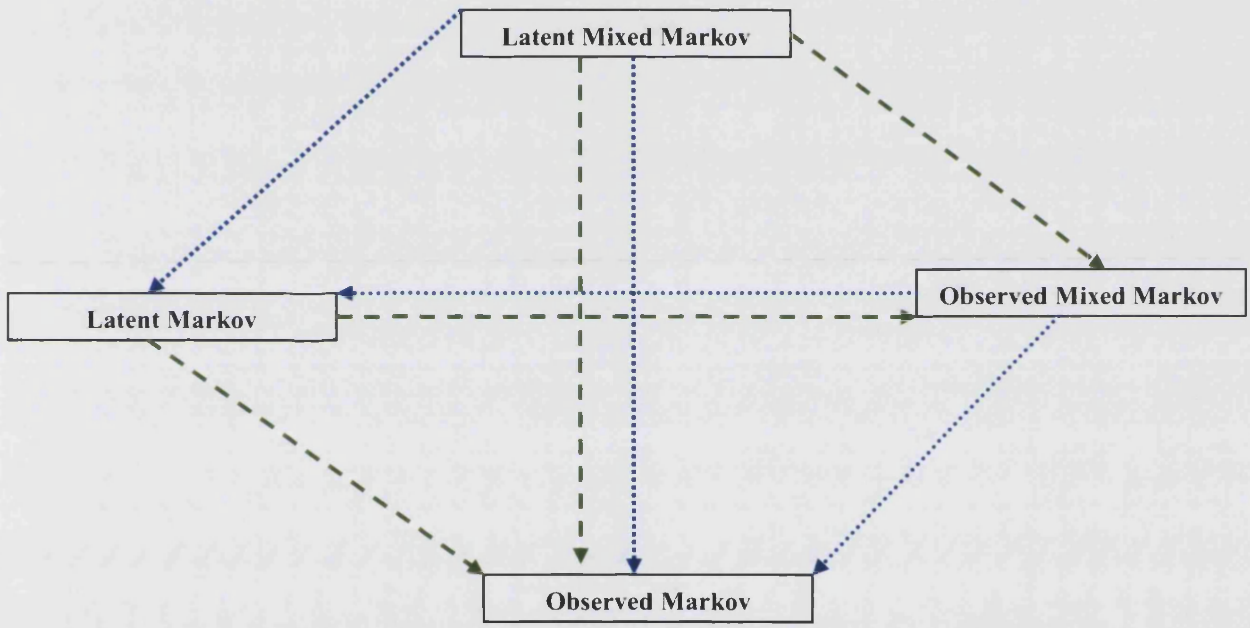
$\rho_{observed|latent}$ are the conditional response probabilities and give the relationship between the observed variables ($x_{91}, x_{92}, ..., x_{02}$) and their latent counterparts (a, $b,...,l$) given chain membership. The matrices of ρ s provide a measure of reliability in the data. If it is equal to the identity matrix, I, the latent variable is perfectly measured by the observed indicators. Deviations of the response matrix from identity, therefore, give the degree of measurement error.

In contrast to the manifest Markov model, the τ s now indicate the transition probabilities between the *latent* variables. The model implicitly treats all change that is not captured by the latent classes as measurement error.

A latent Mover-Stayer model can be derived from (5) by setting constraints on the latent transition probabilities in the stayer chain ($\tau_{b|a} = 0$ if $b \neq a$ and $\tau_{b|a} = 1$ if $b=a$).

The hierarchy of Markov chain models is summarised in Figure 5.1. It shows that the latent mixed Markov model is the most general model. All the preceding models can be derived from it by changing assumptions about the number of chains and the presence of measurement error. The structural components of the latent Markov and latent mixed Markov are the direct analogues of the manifest Markov and mixed Markov. The observed models can be considered as having latent structures but with the response matrices equal to the identity matrix (i.e., no measurement error).

Figure 5.1: A hierarchy of Markov chain models with assumptions



Source: Adapted from Langeheine and van de Pol (2002, p. p. 305)

Key

From population heterogeneity to homogeneity: the number of chains (s) is reduced to 1

No measurement error: response probabilities (ρ =1)

5.5 Assessing model fit for latent Markov chain models

After estimates of model parameters have been obtained, the next step is to assess to what extent each model fits the data. This section discusses three goodness-of-fit measures for testing the hierarchy of Markov model described above, namely, i) the likelihood ratio chi-square test, ii) the Bayesian information criterion statistic, and iii) the dissimilarity index.

i. The likelihood ratio chi-square test

In order to evaluate whether the specified models adequately reproduce the observed frequency tables, the estimated expected frequencies are compared to the observed frequencies. The most widely used goodness-of-fit test is the likelihood ratio chi-square test (G^2), which is calculated from the logarithms of the ratios between observed and expected frequencies. For a model, *M*, derived from a two-dimensional frequency table, G^2 is calculated as follows:

$$G^2(M) = 2\sum f_{ij} \log\left[\frac{f_{ij}}{F_{ij}}\right] \tag{6}$$

where f_{ij} is the observed cell frequency in cell *ij* and F_{ij} is the expected cell frequency of cell *ij*. G^2 tests the null hypothesis that there is no difference between observed pattern frequencies and the estimated expected pattern frequencies postulated by the model (i.e., that the model fits well). Large values provide evidence of a lack of fit. For large sample sizes, the statistic is assumed to be asymptotically distributed as chi-square with $N\text{-}1\text{-}P$ degrees of freedom, where N is the number of cells and P the number of free parameters. In this case, asymptotic means that the sample size tends to infinity with the number of cells fixed, thus, the number of observations in each cell of the observed cross-tables should be large.

G^2 can also be used for testing the relative fit of nested models. This tests the deviance of the model, i.e., whether the additional parameters in the full model, (M_f), explain a significant additional amount of variance in the table compared with a reduced model, (M_r). This is a test of the null hypothesis that the additional parameters equal zero and is calculated as $G^2(M_r) - G^2(M_f)$. This test also follows a chi-square distribution with as many degrees of freedom (*df*) as the difference between those of the both models (df_r-df_f).

ii. The Bayesian Information Criterion statistic

A limitation of G^2 is that when the number of cases in the frequency table become large, small differences between observed and expected tables may be reported as statistically significant, even when the differences may be substantively meaningless, thus yielding a false impression of the explanatory importance of additional variables. Schwarz (1978) recommends the Bayesian information criterion (BIC) for discriminating among competing models, particularly those that are non-nested. It aims to balance goodness-of-fit and parsimony and is based on the difference between G^2 and a "penalty" term, which is a function of the number of parameters (P) in the model and sample size (N):

$$BIC = G^2 - P \log N \tag{7}$$

The first term measures the improvement in model fit that is gained from additional parameters. The second term acts as a counterbalance to increasing model complexity by imposing a penalty for the addition of more parameters. The addition of extra parameters is only desirable if the resulting increase in fit is larger than the penalty for a more complex model. The model with the smaller BIC provides a better fit to the data.

iii. The Dissimilarity Index

Another common estimate for model fit is the dissimilarity index (D.I.), which is a descriptive measure of model fit. It aims to quantify model fit by estimating the smallest fraction of the sample that would need to be reclassified in order to make the model fit exactly (Kuha and Firth, 2005). An advantage of this index is that it is readily interpretable and as it identifies the "best" model based the extent of departure of the observed data from the model (i.e., the percentage of misclassified cases). D.I. is calculated as follows:

$$D.I. = \frac{1}{2}\sum_{i=1}^{n}\left|f_{ij} - F_{ij}\right| \cdot 100 \tag{8}$$

where f_{ij} is the observed frequency in cell *ij and* F_{ij} is the estimated cell frequency in cell *ij*. The index lies between values of 0 and 100, with larger values indicating greater misclassification. A limitation of this index is that there are no strict criteria for determining what an acceptable or good value is. Descriptive measures of fit are widely used to supplement rather than replace model-selection criteria based on the log likelihood (Kuha and Firth, 2005, p.p.3).

5.6 Hypotheses

This section sets out the hypotheses that are tested in this chapter. They draw upon the theoretical literature on poverty dynamics discussed in Chapter 2 (namely, the democratisation, temporalisation, and persistent poverty theories) in addition to the methodological literature on poverty mobility discussed in Section 5.2.

i. Poverty transitions over time can be charaterised by a non-stationary Markov process

To establish the dependence of poverty states between consecutive time periods, the fit statistics of a single chain observed Markov model will be compared with an independence model. The latter makes the extreme assumption that poverty status in one time period is independent of the state occupied in a previous period. Thus the following hypotheses will be tested:

H_0: Poverty status at $t+1$ is independent of poverty status at t : $\tau_{x_{t+1}|x_t} = 0$

H_A: Poverty status at $t+1$ is dependent upon poverty status at t : $\tau_{x_{t+1}|x_t} > 0$

To establish whether the transition probabilities vary over time, the fit statistics of the stationary Markov model will be compared with the non-stationary variant:

H_0: Transition probabilities are stationary: $\tau_{x_{92}|x_{91}} = \tau_{x_{93}|x_{92}} =,\ldots,= \tau_{x_{02}|x_{01}}$

H_A: Transition probabilities are non-stationary: $\tau_{x_{92}|x_{91}} \neq \tau_{x_{93}|x_{92}} \neq,\ldots,\neq \tau_{x_{02}|x_{01}}$

The establishment of non-stationarity is useful as it allows the trends in transition probabilities to plotted over time, thus, an examination of whether and how poverty entries, exits, or persistence has changed.

ii. Measurement error overstates poverty mobility and understates persistence

Based on the literature on poverty mobility, it is hypothesised that the observed data overstates poverty mobility and understates persistence due to the presence of measurement error in income data. To establish the presence of measurement error, the fit of several variants of the latent Markov models (single chain, mixed, and Mover-Stayer) will compared with their observed counter-parts through the inclusion of the conditional response probabilities, ρ , which provide a measure of reliability in the data.

The closer the response probability matrix is to the identity matrix, the more closely are the latent variables are measured by the observed indicators, thus, the smaller the measurement error in the income data.

H_0: The latent variables are perfectly measured by the observed data: $\rho = I$

H_A: The matrix of response probabilities deviates from the identity matrix, thus, the latent variables are imperfectly measured by the observed data: $\rho \neq I$

iii. Democratisation of poverty

The democratisation thesis argues that as a greater number of people are faced with greater social and economic risks, it has become more difficult to distinguish typical poverty profiles. Poverty is related more to personal biographies and is no longer the domain of a clearly identifiable marginalised group defined by structural factors. Instead, it extends more widely across society, if only temporarily (Leisering and Leibfried, 1999). This does not mean that all people face the same risk of poverty, but that no group is protected from it. If there has been a democratisation of poverty, it is expected that the population does not share a single trajectory of poverty dynamics over time. Instead, it is heterogeneous with respect to the experience of poverty mobility. In terms of the model parameters, the hypotheses are expressed as:

H_0: The population shares the same poverty trajectory over time and can be described by a single chain Markov model: $s = 1$.

H_A: The population is comprised of heterogeneous poverty experiences and can be described by a mixed Markov model with more than one chain: $s > 1$

iv. Temporalisation versus persistent poverty

According to the individualisation thesis, poverty in post-industrial societies has become both *temporalised* and *democratised* (Leisering and Leibfried, 1999). Temporalisation means that as life courses have become increasingly individualised, poverty is no longer a fixed or long-term condition, but a temporary phase in the life-course. If the temporalisation thesis holds true, it is expected that the proportion of individuals who experience poverty at least once is relatively high.

If poverty is a more widely shared event in the population, a greater proportion of individuals should be experiencing short spells of poverty and relatively few longer, persistent spells. Consequently, poverty is overcome quickly by those who experience it, and as such, it is expected that there is a high turnover of entries into and exits out of poverty.

A counter-hypothesis to the temporalisation and democratisation theses is that of persistent poverty, which encompasses 'underclass' and cumulative disadvantage theories. This posits that certain groups of people are predisposed towards staying poor due to cultural, behavioral, or structural factors, which leads to downward spirals of deprivation. These theories focus on the routes into poverty and not on the routes out. Thus, poverty is viewed as long-term and largely static.

The Mover-Stayer variant of the mixed Markov model is important in the context of modeling poverty transitions as it allows for testing of the democratisation, temporalisation, and persistent poverty hypotheses. In this model, temporalisation of poverty can be characterised by the 'mover' chain in which there is a high turnover of short-term transitions into and out of poverty between consecutive time points. Persistent poverty can be characterised by the 'stayer' chain in which there are two groups who never experience poverty and those who always experience poverty. The relative size of the chains provides evidence for whether the temporalisation or persistent poverty hypotheses describe the process of poverty dynamics over time. Thus, if the temporalisation hypothesis is true, it is expected that the proportion of individuals belonging to the 'mover' chain is relatively larger than the proportion of poor individuals belonging to the 'stayer' chain:

Temporalisation: $\Pr(\hat{\pi}_{s=movers}) > \Pr(\hat{\pi}_{s=stayers})$

Persistent poverty: $\Pr(\hat{\pi}_{s=movers}) < \Pr(\hat{\pi}_{s=stayers})$

5.7 Empirical results

The results of the hypotheses testing are presented in two parts:

i. Hypotheses i to iii are tested by a hierarchical model-building strategy in which the fit of an independence model is improved upon by introducing the assumptions of a Markov process, population heterogeneity and measurement error into the models. Each type of model is introduced by assuming that poverty transitions from one wave to the next are stationary. The validity of this assumption is tested by comparing the fit of this model with one allows transition probabilities to vary over time.
ii. Hypothesis iv is tested by presenting the model parameters of the best-fitting model.

5.7.1 Assessing model fit

Tables A5.2, A5.3, and A5.4 in the Appendix present the fit statistics for each of the nine models for the population and children, respectively. Twelve repeated measurements of the dichotomous poverty indicator results in a transition table of 4096 ($= 2^{12}$) cells. Poverty status is measured relative to 60 per cent median income.

The statistical program package, PANMARK (van de Pol et al., 2000) is used as it allows the estimation of the various Markov models described in Section 5.4. Alternative programs for estimating Markov models include LEM (Vermunt,(1997)) and WinLTA (Collins et al., 2002).

i. Poverty transitions over time can be charaterised by a non-stationary Markov process

In order to test for dependence of poverty states between consecutive time points, an independence model is first fitted, which assumes that there is no association between poverty measures across time, and as such, serves as a benchmark model for establishing the presence of a Markov process in subsequent models. The fit statistics are presented in Table A5.2. As expected, the independence model fits very poorly for both samples according to G^2 for both samples (p=0.0000). The index of dissimilarity shows that 48 per cent of the cases are misclassified for the population and 39 per cent for children. This suggests that there is an association between poverty at different time points. This is formally tested by introducing the single chain observed Markov model (Table A5.3), which assumes that the poverty state occupied by a respondent at $t+1$ depends on the state occupied at t. Model 2 restricts transition probabilities to be equal, whereas Model 3 allows for non-stationary transitions.

The p-values for both models and for both samples show a poor fit for the population. The introduction of time heterogeneity results in a statistically significant decrease in the deviance for both samples (Population: Model 2- Model 3: G^2=72.31, d.f.=20, p=0.0000; Children: G^2=43.34, df=20, p=0.0018) and a slightly better BIC relative to the stationary version, however, the fit is still inadequate. The index of dissimilarity for both models shows that whilst there has been a reduction in the proportion of misclassifications compared to the independence model, the magnitude of departure is approximately 30 per cent. These findings suggest that members of both samples do not follow the same underlying poverty trajectory.

ii. Democratisation of poverty: presence of population heterogeneity

The presence of population heterogeneity is tested using a mixed Markov specification (Models 4 and 5, Table A5.4), which introduces two Markov chains. The transition probabilities of one of the chains are restricted to be an identity matrix, yielding the Mover-Stayer model. The p-values of G^2 show a poor fit to the data for both samples, however, the dissimilarity index shows that misclassifications have been reduced by 50 per cent for the population and 60 per cent for children relative to the simple Markov model. The introduction of non-stationary transition probabilities leads to an improved description of the data (Model 4-Model 5: Population: G^2=74.37, df=20, p=0.000; Children: G^2=126.05, df=20, p=0.0000).

Furthermore, there is a significant gain in fit over the single chain Markov model (Model 3-Model 5: Population: G^2=1701.53, df=2, p=0.0000; Children: G^2=491.02, df=2, p=0.0000). These findings provide evidence for the heterogeneity, and thus the democratisation, of poverty experiences within the population.

iii. Presence of measurement error

Thus far, it has been established that the population is heterogeneous with regards to poverty mobility, and that there is dependency between poverty states over time. The next set of models tries to improve upon the fit of the observed models by introducing latent variables, which represent "true" poverty status corrected for measurement error by taking into account the probabilistic relationship between latent and observed variables.

The time heterogeneous latent Markov model fits the data very well for both samples. Comparison with the simple manifest Markov model shows that the incorporation of measurement error provides a better description of the data (Model 3-Model 7: Population: G^2=2277.75, p=0.0000; Children: G^2=514.70, p=0.0000). Fit statistics from the observed models indicated that the population is heterogeneous with regards to poverty transitions, thus, the inclusion of measurement error alone in the single-chain latent Markov model may be not sufficient to achieve adequate model fit. Latent variables are incorporated into the Mover-Stayer model (Models 8 and 9). The non-stationary version shows the best fit to the data for all three statistics and for both samples and a statistically significant gain in fit over the observed Mover-Stayer model (Model 4-Model 8: Population: G^2=1071.14, df=4, p=0.000; Children; G^2=134.25, p=0.000).

Tables A5.7 and A5.8 in the Appendix present the estimated parameters of the non-stationary latent Mover-Stayer model for all individuals and children, respectively. The extent of measurement error can be gauged from the response probabilities ($\hat{\rho}$), which give the conditional probabilities of an observed response given class membership and show the degree of measurement error in both chains. The diagonal elements of the matrix show the reliabilities, whereas the off-diagonal elements show error. Measurement error is of a similar magnitude for both samples but is lower for stayers than movers. Non-poor movers and stayers are almost perfectly identified for both samples. The greatest source of error is due to misclassification of true poor movers as non-poor (20-25 per cent), which is approximately twice the corresponding figure for stayers.

As shown by Table 5.3 in the descriptive analysis, it is expected that there are relatively more misclassifications among the poor, given that a large proportion of the poor have incomes just below the poverty line relative to the non-poor, the majority of whom have incomes located further away from the poverty line.

iv. Temporalisation versus persistent poverty

The $\hat{\pi}$ coefficients of the latent Mover-Stayer model (Tables A5.7 and A5.8 in the Appendix) give the proportions of movers and stayers. Class 1 and Class 2 denote the latent analogues for poor and not-poor, respectively. The estimates indicate considerable poverty mobility with approximately half of all individuals and children belong to the mover chain. Given the assumption of a Markov process, members experience short episodes of poverty, either staying poor for two consecutive years, or entering or exiting it at $t+1$. These findings lend support to the temporalisation hypothesis.

The remaining half of both samples is identified as stayers, either staying continually in our out of poverty. With regards to the persistence hypothesis, the findings show that only a very small minority of individuals stay poor for the entire twelve years. The initial probabilities, $\hat{\delta}^1$, show the proportions of movers and stayers that are identified as poor or non-poor at the first period. Over 90 per cent of stayers are non-poor. The product of $\hat{\pi}$ and $\hat{\delta}^1$ gives the proportion of individuals who are always poor or always non-poor. Thus, 3.2 per cent of all individuals and 3.9 per cent of children are estimated to be constantly poor. Whilst this positive finding suggests that the persistence hypothesis cannot be accepted in a strict sense, the results give cause for concern. The descriptive analysis shows that a non-negligible proportion of individuals do remain in poverty for a sufficiently long enough period for it to possibly have a scarring effect on their lives. For example, 6 per cent of children experienced poverty at least eight times. It is likely that the frequent recurrence of poverty is highly detrimental to children's standards of living given that changes incomes for a large proportion of the poor are not sufficiently large enough to keep them out of poverty for a long enough to improve welfare. Furthermore, the presence of measurement error overstates mobility, and consequently understates persistence in observed transition tables.

In summary, whilst the introduction of the Markov assumption leads to a reduction in G^2 and the dissimilarity index relative to the independence model, the model fit for both samples was poor. This does not mean that there is lacks of dependence between poverty states over time but that a homogeneous trajectory is an inappropriate description of poverty dynamics in the population, as shown by the better fitting mixed Markov model. A comparison of the fit statistics for all nine models showed that the non-stationary latent Mover-Stayer model was the best fitting model for both samples. The findings confirm that poverty transitions measured solely at the observed level are an inadequate reflection of the data as measurement error causes a substantial deviation between the model and the data. The latent Markov Mover-Stayer model highlights a paradoxical characteristic of poverty dynamics: poverty is simultaneously temporalised due to a large amount of *short-term* mobility arising from individuals entering and exiting poverty over time (as characterised by the mover chain), together with persistence due to a minority who experience uninterrupted episodes of *long-term* poverty (as characterised by the mover chain).

The next section presents the trends in estimated transition probabilities from for the latent Mover-Stayer model. In order to gauge the impact of measurement error on poverty mobility rates, the observed Markov parameters are also presented.

5.7.2 Trends in poverty transition probabilities: observed and error-corrected estimates

The latent transition probabilities ($\hat{\tau}$) for the movers' chain (Tables A5.7 and A5.8 in the Appendix) show the true rates of poverty mobility. The diagonal elements of the stayers' matrices are, by definition, fixed at a probability of one. Over 70 per cent of individuals belonging to the mover chain stay poor at two consecutive waves, and over 90 per cent stay non-poor. In order to take account of chain sizes, $\hat{\pi}$, a weighted sum of probabilities for each cell of the movers' and stayers' transition matrices can be calculated, which gives a picture of overall error-corrected transition probabilities. As the row probabilities sum to unity, the proportion of the mobile population is one minus the always poor or always non-poor. Findings are, therefore, discussed in the context of short-term poverty persistence (where individuals are poor at two consecutive time points) and poverty entry. The weighted sums of probabilities are presented in tables A5.9, A5.10, and A5.11 in the Appendix and are calculated as follows:

Short-term persistent poor:

$$Pr(Poor_{t+1} \mid Poor_t) = \left(\hat{\pi}_{s=mover} * \hat{\tau}^{mover}_{class1,t+1|class1,t}\right) + \left(\hat{\pi}_{s=stayer} * \hat{\tau}^{stayer}_{class1,t+1|class1,t}\right)$$

(Example of calculation using Table A7: $Pr(Poor_{'92} \mid Poor_{'91}) = (0.469*0.741)+(0.531*1)=0.879$)

Poverty entry:

$$Pr(Poor_{t+1} \mid Not\text{-}poor_t) = \left(\hat{\pi}_{s=mover} * \hat{\tau}^{mover}_{class1,t+1|class2,t}\right) + \left(\hat{\pi}_{s=stayer} * \hat{\tau}^{stayer}_{class1,t+1|class2,t}\right)$$

(Example of calculation using Table A7: $Pr(Poor_{'92} \mid Not\text{-}poor_{'91}) = (0.469*0.110)+(0.531*0)=0.052$)

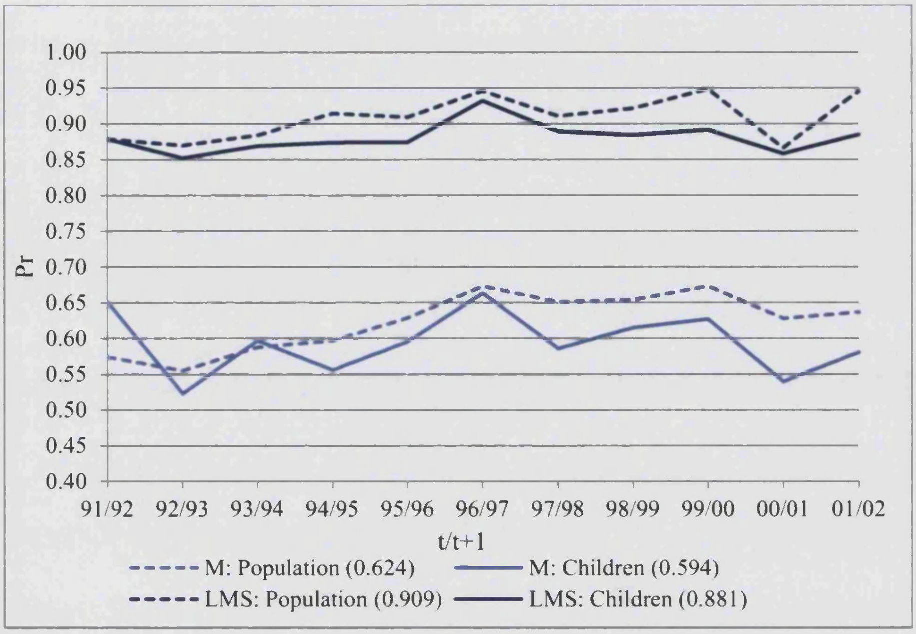
i. Trends in short-term poverty persistence

Figure 5.2 compares the trends in observed and latent transition probabilities from t to $t+1$ for both samples. The figures in brackets show average probabilities over the entire period. To check for the robustness of the findings to the poverty line, persistence probabilities are also plotted using the 50 and 70 per cent of median income thresholds. These can be found in the Appendix (figures A5.1 and A5.2).

At each poverty line, the shapes of the error-corrected latent trajectories (that is, probabilities that arise from the latent Mover-Stayer model) broadly follow a similar pattern to the observed trajectories, and are of a similar magnitude for both samples (although children tend have lower persistence probabilities than the population). The error-corrected estimates show that poverty persistence between two periods is very strong. At the 60 per cent threshold, it increased from 88 percent to approximately 94 percent for both groups between 1991/1992 and 1996/1997. By the 2001/2002 transition, it fell to its original level for children but remained unchanged for the population. Over the entire period, error-corrected poverty persistence is higher than the observed estimates for all poverty lines. For example, at the 60 per cent threshold, latent probabilities are, on average, 50 per cent higher than observed estimates for both samples. Thus, those who were poor in one year were more likely to be poor the following year than to escape it and this is particularly magnified once measurement error has been controlled for.

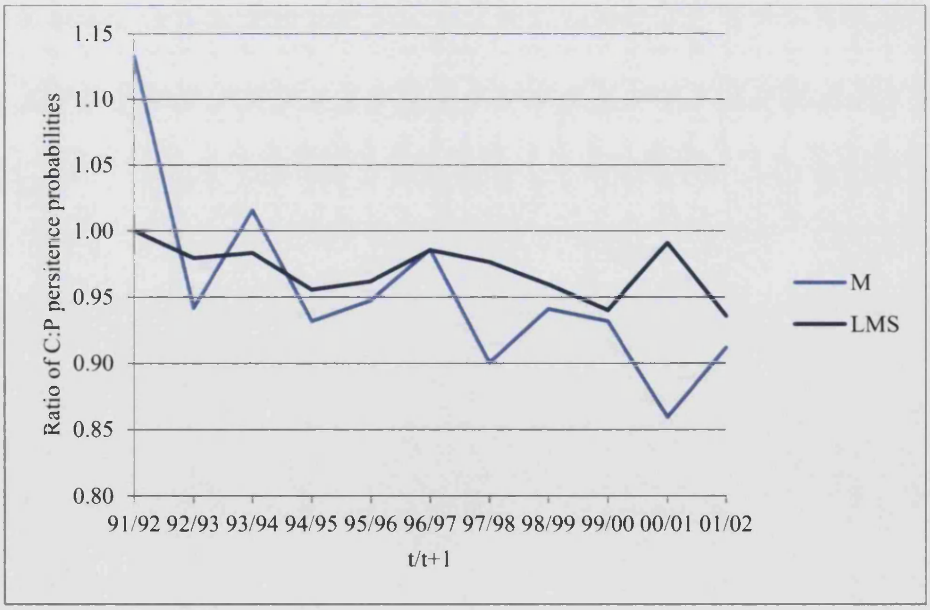
Figure 5.3 charts the change in the ratio between children and the population persistence probabilities. Both observed and error-corrected ratios show that children experienced a decline in the probability of staying poor in two consecutive years relative to the population.

Figure 5.2: Observed and error-corrected poverty persistence probabilities: 60 % poverty line



Source: Derived from parameters in tables A5.5 and A5.6 for the observed Markov (M) probabilities, and tables A5.8 and A5.9 for the error-corrected latent
Mover-Stayer (LMS) probabilities. LMS probabilities are based on weighted sum of mover and stayer chains. Figures in brackets denote average transition probabilities over the entire period.

Figure 5.3: Ratio of children to population persistence probabilities: 60% poverty line



Source: Derived from parameters in tables A5.5 and A5.6 for the observed Markov (M) probabilities, and tables A5.8 and A5.9 for the error-corrected latent Mover-Stayer (LMS) probabilities.

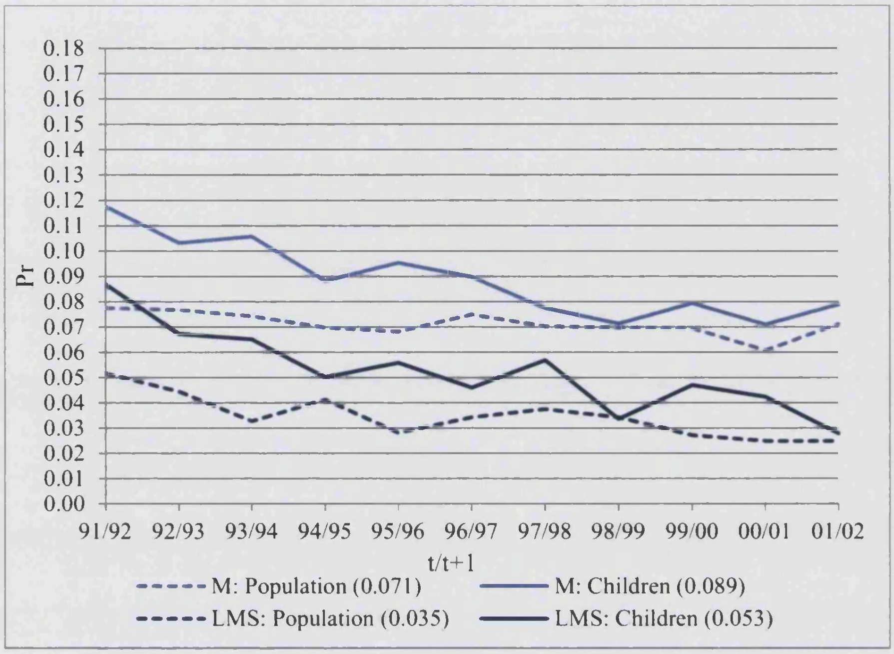
ii. Trends in poverty entry

Figure 5.4 shows the trends in poverty entry probabilities for the 60 per cent poverty line. Figures A5.3 and A5.4 in the Appendix show the sensitivity of the results at the 50 and 70 per cent poverty lines.

At all thresholds, poverty entry was over-estimated in the observed data. The observed and error-corrected estimates show that children were more likely than all individuals to enter poverty. An increase in the poverty line cut-off was associated with an increase in the probability of entry. At the 60 per cent threshold, latent transitions are, on average, half the observed ones.

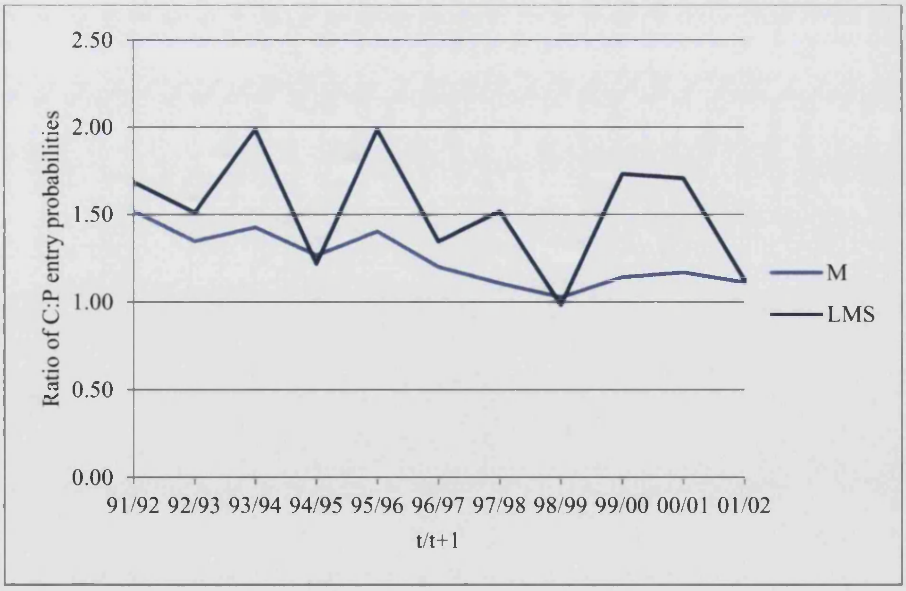
This risk of poverty entry was fairly stable for all individuals at all thresholds, however, at the 60 per cent and 70 per cent poverty lines, there was a declining trend in poverty entry for children. This can also be seen in Figure 5.5, which charts the ratio of children to population entry probabilities. At the 50 per cent threshold, the risk of entry for children increased slightly between 1991/1992 and 1997/1998. After this period, children's risk tended to converge towards, or was close to, the risk level of all individuals for all three poverty lines. According to the latent estimates, true rates of poverty entry for children declined by two-thirds from 9 per cent to 3 per cent between the first and last transition periods (60 per cent threshold). For the population, this figure halved from 5 per cent to 2.5 per cent. Thus, whilst the risk of entry for children fell at a faster rate relative to all individuals, the reduction experienced by the latter was already from a low risk at the beginning of the period. The findings simultaneously imply that a greater proportion of children were persisting in non-poverty over the decade.

Figure 5.4: Observed and error-corrected poverty entry probabilities: 60 % poverty line



Source: Derived from parameters in tables A5.5 and A5.6 for the observed Markov (M) probabilities, and tables A5.8 and A5.9 for the error-corrected latent Mover-Stayer (LMS) probabilities.
LMS probabilities are based on weighted sum of mover and stayer chains.
Figures in brackets denote average transition probabilities over the entire period.

Figure 5.5: Ratio of children to population entry probabilities: 60% poverty line



Source: Derived from parameters in tables A5.5 and A5.6 for the observed Markov (M) probabilities, and tables A5.8 and A5.9 for the error-corrected latent Mover-Stayer (LMS) probabilities.

5.8 Conclusion

This section concludes by i) summarising the findings and ii) highlighting the limitations of latent Markov chain modelling.

i. Summary of the findings

Latent Markov analysis is a relatively new technique in poverty dynamics research. There are several advantages associated with the estimation of such models. Firstly, and most importantly, the panel model takes into account the time dependency between observations. As the descriptive statistics show that most of the ever poor people exit poverty after one year, the assumption of a Markov process for modelling short-term transitions is appropriate.

The approach also allows the estimation of a wide choice of models by changing the assumptions about the stationarity of transitions over time, population heterogeneity, and measurement error. This provides a richer account of the underlying dynamics of poverty for various sub-groups and countries that go beyond simple turnover tables. Latent Markov modeling also shows the size of each latent category and the extent to which transitions take place from one latent category to another. Thus, the technique not only summarizes the underlying process of poverty dynamics, but makes it possible to estimate the 'true' rates of mobility adjusting for measurement error.

In terms of the findings, the descriptive statistics showed that the vast majority of individuals never experienced poverty, although this was less likely for children than the general population. Only a minority experienced long, uninterrupted episodes. In between these extremes, there was a high degree of poverty mobility. The probability of experiencing poverty at least once was high (particularly among children) and almost double the cross-sectional rate. Furthermore, poverty was shown to be unlikely as a one-off event as the risk of reoccurrence in the future remains high.

The relationship between poverty transitions and the income distribution provides a partial explanation for the high degree of fluidity of transitions. Most transitions are to adjacent income groups, and a large proportion of individuals who have exited poverty or have fallen into it have incomes near the poverty line. As a consequence, poverty 'churning' around the threshold is high. A second explanation for the high level of poverty mobility is the presence of measurement error in the income data, which leads to an overstatement of mobility in the observed data.

In order to derive 'true' rates of poverty transitions for the population and for children, the analysis proceeded by fitting a hierarchy of Markov models adjusting for assumptions related to the stationarity of transitions, heterogeneity in transition patterns, and measurement error. It was found that a latent Mover-Stayer model provided the best description of poverty dynamics for both groups. The presence of different chains in the latent Mover-Stayer model and the various patterns of mobility within these chains suggests (albeit, in a simplified way) that the population is heterogeneous with regards to the experience of poverty mobility, thus supporting to the hypothesis of a democratisation of poverty.

The fit statistics indicated that there is no evidence that the underlying process of poverty dynamics differed for children compared to the general population. However, children experienced different trends in transition probabilities compared to all individuals.

Two salient findings that are consistent with previous research are the presence measurement error is significant in poverty mobility data. Secondly, observed transition probabilities exaggerate the magnitude of poverty mobility and under-state poverty persistence compared to latent transition probabilities.

The trends in transition probabilities showed that the risk of entering poverty remained static for the general population. Before 1997, children were more likely than the general population to enter poverty, and after this period, entry risks converged towards population levels. This reflects the greater reduction in cross-section sectional child poverty post-1997. Less progress was made in lifting children out of poverty. Although children were increasingly less likely than the population to persist in poverty after 1997, the vast majority remained poor between two consecutive years. Furthermore, the risk of persistence in 2000/2001 stood at a similar level to a decade earlier. These findings were robust to the specification of the poverty line.

In summary, the descriptive analysis and estimates from the latent Markov Mover-Stayer model has confirmed a paradoxical characteristic of poverty dynamics: poverty is simultaneously characterised by a large amount of *short-term* mobility, which lends support for the temporalisation hypothesis, due to individuals entering and exiting poverty over time (as characterised by the mover chain), together with a small minority who experience uninterrupted episodes of *long-term* poverty (as characterised by the stayer chain), which lends some support for the persistence hypothesis.

This chapter modeled poverty dynamics as a short-term Markov process. However, the combination of measurement error in income data (which understates poverty persistence) and the clustering of poverty entries and exits close to the poverty line suggests that a greater proportion of individuals may be experiencing poverty for longer periods of time than these observed data suggests.

ii. Limitations of latent Markov modeling

With regards to the limitations of specific assumptions of latent Markov models, only first-order transitions are taken into account. This assumption may be too simplistic if the process has a long memory, i.e., if some people have a persisting probability to return to previous states. Indeed, there is much evidence that duration dependency over longer time periods is important with respect to poverty (Bane and Ellwood, 1986; Jenkins and Rigg, 2001). Higher order Markov chain models, however, add complexity to modelling associations in the data due to the additional parameters and are more difficult to interpret than first-order models (Langeheine and van de Pol, 2002).

Taking only dualistic heterogeneity into account may also be too simplistic, either because greater heterogeneity in the experience of poverty may exist or because these experiences are "fuzzy", with some people that are close to either type, but that do not quite fit in. Although increasing the number of chains may lead to a better fit of the data, a caveat is that the model becomes more difficult to interpret and the number of parameters to be estimated increases when latent variables are included. A two-chain latent Mover-Stayer model provided an excellent fit to the data and allows comparison with previous research that has used this model. Finally, it is conceptually relevant in describing short-term persistence and mobility in the context of individualisation and persistence theories of poverty.

The use of statistical techniques to model poverty transitions necessitates that assumptions are made about the structure of measurement error. In latent class models, it is assumed that errors are not serially correlated. However, data on income from the U.S. suggests that measurement error in an individual's income has positive autocorrelation across waves of a panel (Bound and Krueger, 1991). This is partly because the effects of incidental income shocks persist over time. If the models had taken this autoregressive component of measurement error into account, it is likely that a greater proportion of the observed poverty transitions could be attributed to real change instead of spurious change. This implies that income mobility could be higher than the latent Markov models predict.

Finally, caution is warranted when interpreting the latent transition probabilities. There may be two sources of error in the observed income data: that arising from non-systematic response errors (e.g., misreporting of income and coding errors), and random events. Latent variable models are unable to make the distinction between someone who is usually poor but at one point in time happens to be erroneously recorded as non-poor and a person who is usually poor but at one point in time happens to experience a temporary rise in income, thereby, lifting him/her out of poverty.

Chapter 6 A Dynamic Regression Analysis of the Determinants of Poverty

6.1 Introduction

The previous chapter established that past experiences of poverty increases the risk of an individual being poor in future periods. Between 1997 and 2002, this risk declined but returned to the same level as a decade earlier. This chapter extends the Markov analysis by investigating the underlying mechanisms for the high persistence rate using a multiple regression framework.

Persistence may arise if previous poverty itself directly affects the future probability of being poor. This is known as structural or "true" *state dependence* (Heckman, 1978). Long periods in poverty may lead to changing attitudes towards work, loss of motivation and confidence, or a depreciation of skills, which increases the likelihood of unstable or low paid employment. Furthermore, poverty may be associated with perverse incentives associated with the welfare system. For example, the receipt of benefits may hinder an unemployed or low paid individual from increasing their income over the amount received from welfare payments or a minimum level if they face greater tax burdens or income deductions (Biewen, 2004).

A second explanation for poverty persistence may instead be due to *individual heterogeneity*. This could arise from observable characteristics that are associated with the risk of poverty, for example, poor education, family size, or employment status. On the other hand, persistence may arise due to time invariant unobserved heterogeneity across (otherwise observationally equivalent) individuals, for example, ability, preferences, and motivation. Furthermore, initial disadvantages may affect people's beliefs about their ability to change their own condition. Thus, unobserved heterogeneity may lead to a sorting effect whereby those with "favourable" characteristics are able to exit poverty after a short period of time, leaving behind a pool of people behind with "adverse" characteristics. An implication of heterogeneity is that individuals who are likely to experience poverty at time t because of (possibly unobserved) adverse characteristics may also be likely to experience poverty in any other period because of the very same adverse characteristics. Furthermore, if these unobservable factors affecting poverty transitions are correlated, then failing to model them could provide biased estimates of the risk of poverty.

Distinguishing between true state dependence and heterogeneity has important policy implications. Individuals, particularly children, who suffer from poverty persistence are more likely to experience other forms of disadvantage throughout the life-course. If true state dependence is relatively more important than heterogeneity, policies could be targeted towards preventing people from becoming poor, as once they are in this state, they are likely to stay poor regardless of their characteristics. On the other hand, if observed heterogeneity is more important in explaining the persistence in poverty, policies could target those characteristics that keep individuals at a high risk of being poor. Finally, if poverty persistence is largely to due to unobserved heterogeneity, then policies aimed at breaking the "poverty trap" via monetary transfers to the poor will be ineffective. They may not be amenable to the adverse unobserved characteristics, therefore, will not reduce the risks of experiencing episodes of poverty in subsequent periods.

This chapter examines the underlying mechanisms through which poverty persists using a dynamic random effects probit model. The remainder of the chapter is organised as follows: Section 6.2 reviews the related literature. The dynamic random effects model is set out in Section 6.3. The hypotheses are set out in Section 6.4. Section 6.5 presents the empirical results. The final section summarises the findings and concludes.

6.2 Previous literature

Previous empirical research has established that individuals who experience poverty have a heightened risk of poverty in the future. In devising effective anti-poverty poverty policies, it is essential to determine who is at risk of experiencing poverty and what factors are associated with persistent poverty.

One of the most common models applied to the study of poverty dynamics controlling for multiple covariates has been the spell or hazard regression approach (Jenkins, 2007). This analyses events that trigger entries into or exits from poverty. Using the single longest observed poverty (or non-poverty) spell as the dependent variable, this approach regresses the duration to exit (or entry) on a set of covariates, which include dummies for duration, and individual and household characteristics (Bane and Ellwood, 1986). Two important findings have emerged from this literature. Firstly, individuals with previous experiences of poverty are at greater risk of poverty than individuals who have never been poor. Secondly, the estimated probability of exiting poverty falls the longer a person stays in poverty. Table 6.1 compares findings for the risk of exiting poverty conditional upon the length of time spent in poverty. Jenkins and Rigg (2001) find that for a cohort of individuals just beginning a poverty spell, the probability of leaving after one year in poverty is equal to one half; after seven years, this declines to one-fifth.

Table 6.1: Risk of poverty exit conditional upon length of time spent in poverty

		Number of years since start of poverty spell						
Study	BHPS waves	1	2	3	4	5	6	7
Antolin *et al.* (1999)[1,5]	1991-1996	0.36	0.25	0.17	0.11	0.07		
Devicienti (2000)[2,5]	1991-1997	0.50	0.4	0.42	0.21	0.06		
Devicienti (2001)[3,5]	1991-1998	0.47	0.37	0.32	0.18	0.16	0.25	
Jenkins and Rigg (2001)[4, 6]	1991-1999	0.54	0.35	0.29	0.26	0.24	0.21	0.19

Sources and notes:

1. Table 9, p.p. 41
2. Table 4, p.p. 2
3. Table 3(b), p.p. 47
4. Table 4.1, p.p. 77
5. Studies use 50 per cent contemporary mean income.
6. Study used 60 per cent contemporary median income.
   These estimates represent the probability of leaving a poverty spell conditional on the length of time already spent in poverty (i.e., the hazard rate).

Single-spell models estimate entry and exit equations separately under the assumption that entry and exit rates can be treated as independent. Stevens (1999) extended this model to estimate exit and re-entry equations simultaneously controlling for unobserved heterogeneity, which leads to more accurate estimates of the duration of poverty. Devicienti (2000, 2001) and Jenkins-Rigg (2001) apply this to BHPS data.

Whilst the spells approach has been important in capturing the effects of duration in or out of poverty, it does not provide explicit estimates of the effect of previous experiences of poverty on the current risk of being poor (i.e. state dependency). Another development has been components-of-variance analysis to income (Lillard and Willis, 1978). Using a specification for the error terms (for example, AR(1)), income or income changes can be decomposed into permanent and transitory components of income, which is useful for looking at income shocks over time. A limitation of this approach is that it assumes that the dynamic process is homogeneous across all income groups (Jenkins, 2000).

An attempt to model poverty transitions in a more structural way was introduced by Burgess and Propper (1998) and applied more recently by Aasve *et al.* (2005). Instead of modelling poverty transitions directly given a set of exogenous variables, the authors estimate simultaneous hazard equations for the underlying processes which determine earnings, such as fertility, marriage, and labour force participation, while allowing the unobserved effects of these equations to be correlated. From the resulting estimates, income and poverty status are then derived from the probability and earnings associated with being in each of the processes. Thus, poverty dynamics are assumed to arise from dynamics of the underlying processes rather than through state dependence of poverty itself. A short-coming of this approach is that simplifies the number of simultaneous risks. Secondly, the processes themselves may be inter-related, leading the problem of endogeneity. Finally, Jenkins (2000, 2007) questions whether the pay-off from a structural approach is worthwhile given that these models are highly complex and time-consuming to implement.

In general, one common finding across these approaches is that past episodes of poverty are an important determinant of current or future poverty. A limitation of these studies is that they provide a limited account of the underlying causal mechanisms in terms of unobserved heterogeneity and true state dependence.

More recently, studies have begun to explore the role of unobserved heterogeneity and state dependence in poverty dynamics, mainly through multiple spell hazard models (Stevens, 1999; Devicienti, 2000; Biewen, 2003; Fertig and Tamm, 2007) and first-order Markov transition models controlling for covariates, which estimate the determinants of poverty conditional on poverty status in the previous period (Cappellari and Jenkins, 2002, 2004; Poggi, 2007). The conventional view has been that differences in observed characteristics explain the differential risks of poverty transitions between different sub-groups, however, these studies challenge this by showing that unobserved heterogeneity and previous experiences of poverty increase the likelihood of current or future poverty independently of observed characteristics. Using a Markov transition probit model and the first nine waves of the BHPS, Capellari and Jenkins (2004) estimate that 58 per cent of poverty persistence is due to genuine state dependence and the remainder is due to individual heterogeneity. Devicienti (2001) applies a multiple-spell hazard model of poverty dynamics to the first eight waves of the BHPS and estimates that 23% of individuals have unobserved characteristics that constrain them to persistent poverty.

Cohort studies have also shed light upon the role of unobservable factors in explaining inter-generational income persistence. Using the NCDS 1958 and BCS1970 cohort data, Blanden, Gregg and Machin (2005) found that the relationship between parental and children's incomes in adulthood had strengthened over time (children born in 1970 were more likely than children born in 1958 to belong to the same earnings quartile in adulthood as their fathers[24]). Blanden, Macmillen and Gregg (2006) extended this analysis by examining the role of key transmission mechanisms in strengthening the elasticity of earnings across generations. Their study is one of the first to investigate unobservable factors in the form of

[24] See Chapter 2 for a more detailed discussion of the findings.

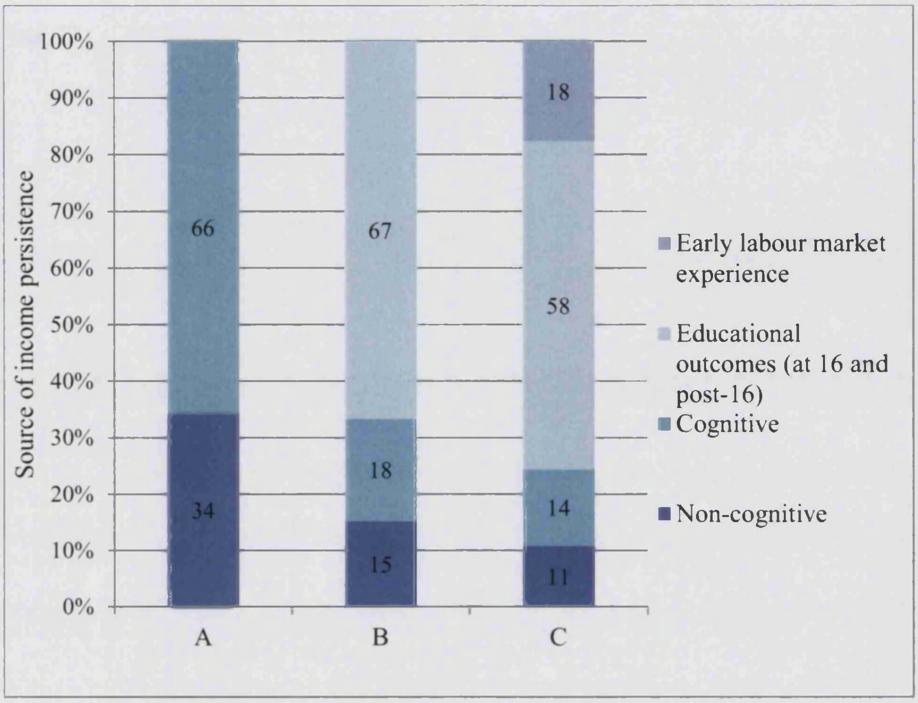
cognitive and non-cognitive[25] characteristics as underlying causes of persistence. Educational attainment and early labour market outcomes were also included as key mechanisms.

Figure 6.1 compares the sequential effect of the various factors in explaining persistence. Educational outcomes are the most substantive drivers of persistence. Cognitive and non-cognitive effects are attenuated substantially in models B and C through the addition of educational outcomes (and less so when labour market experience is added). Whilst they account for approximately a quarter of persistence in model C, this is non-trivial given that it is the direct contribution over and above the indirect effects operating through education.

The authors also conducted a similar analysis for the cohort of children born in 1958 using the NCDS in order to ascertain why income persistence had increased between both generations. 80 per cent of the increase in persistence could be explained by the four factors. Three main factors contributed to this rise: access to higher education, attainment at age 16, and labour market attachment became much more strongly related with family income. One striking finding was that non-cognitive variables were strongly associated with parental income in the 1970 cohort, but not in the 1958 cohort. Whilst the relationship of non-cognitive variables with family background strengthened, the effect was mainly mediated through educational attainment. Cognitive ability was not important in explaining changes in mobility.

[25] Cognitive indicators are measured at ages 5 and 10/11 and include recognition, reading, maths, and general ability scores. They are used as proxies for inherited intelligence and investments by better educated parents in their children. Non-cognitive indicators include behavioral and personality traits such as self-esteem, anxiety, concentration, extroversion. See Blanden, Macmillen and Gregg (2006) Table A1, p.p. 28-29 for a more detailed description of these variables.

Figure 6.1: Composition of inter-generational income persistence: BCS 1970



Source: Blanden, Macmillen and Gregg (2006). Derived from Table 3, p.p.18
Model A accounts for 29 per cent of the association between parental income and children's earnings for the 1970 cohort. The corresponding figure for Model B is 46 per cent and Model C 54 per cent. The bars represent fractions of these figures.

6.3 Regression modeling

6.3.1 Dynamic random effects probit

This section describes the dynamic random effects (DRE) probit model for deriving the determinants of poverty. [26] This model allows one to test the effect of past poverty on current poverty controlling for individual heterogeneity, either observable or unobservable. [27] Two shortcomings of the random effects specification is that of correlated individual effects and the 'initial conditions' problem, which can lead to

[26] Dynamic random effects models were developed in the unemployment dynamics literature (Heckman, 1981; Arulampalam, Booth & Taylor, 2000) and have recently been applied to the dynamics of social exclusion (Poggi, 2007) and happiness (Lee & Oguzoglu, 2007).

[27] There are notable differences between dynamic random effects models and hazard models, which have been used frequently to analyse poverty dynamics. Dynamic random effects model measures the magnitude of state dependence through the inclusion of lagged poverty status. Thus, it captures how the experience of poverty in one year increases the risk of poverty in the next year. In contrast, hazard models measure duration dependence (how the likelihood of exiting poverty decreases the longer one remains in poverty). This is captured through a series of time-dummies as explanatory variables and uses length of the poverty spell as the dependent variable.

biased and inconsistent estimators in addition to incorrect inferences about the magnitude of true and spurious state dependence. Both problems are discussed along with solutions.

The effects of unobserved heterogeneity can either be assumed as random variables, referred to as the random effects model, or fixed parameters, referred to as the fixed effects model. In the random effects approach, the distribution of the individual specific effect is parameterised conditional on exogenous explanatory variables. In the fixed effects approach, one attempts to estimate the parameters making only minimal assumptions about the individual specific effects.

When the unobserved individual specific effect affects the outcome linearly, one can avoid the consideration of random versus fixed effects specification by eliminating them from the specification through some transformation or to integrate it out. However for the binary-choice fixed effects model, no general rule or practical transformation exists and one has to consider the specific structure of the non-linear model to derive such a transformation (Hsaio, 2003). Honore and Kyriazidou (2000) proposed a semi-parametric estimator for the fixed effects logit model. The advantage of this approach is that the time constant unobserved effect is removed such that no assumptions about the endogeneity of the unobserved effects need to be made. However, this flexibility has several drawbacks, one of them being that partial effects are not identified, which is crucial for determining the amount of state dependence (Wooldridge, 2005). Secondly, the estimator imposes severe restrictions on the data due to the "incidental parameter problem" in which the number of individual-specific dummy parameters grows with the size of the data. Finally, it is also unable to obtain the coefficient estimates of time- invariant explanatory variables. Based on these limitations, this study utilises a random effects probit specification.

For an individual i, the dependent variable, y_{it}, represents measured poverty status at time t, taking the value 1 if the individual is poor, and 0 otherwise. The basic dynamic model depicting poverty status is presented in equation (1)[28] and is a function of three main components, namely observed characteristics, poverty status in the previous time period, and unobserved individual heterogeneity:

$$y_{it} = x_{it}\beta + \gamma y_{it-1} + v_{it}, \qquad (1)$$

$$y_{it} = 1\ (y_{it} > 0) \qquad (2)$$

[28] The random effects probit model is used instead of the logit model as random effects give rise to correlations among the successive disturbances. Thus, the multivariate normal distribution is more flexible than the logistic distribution, which requires that all correlations are equal to 0.5 (Maddala, 1987).

$$v_{it} = \alpha_i + u_{it} \qquad (3)$$

where $i = 1,2,...N$

$\alpha_i \sim N(0,\sigma_\alpha^2),\ u_{it} \sim N(0,1)$

N = sample size

$t = 1,2,...,12$ annual measurement occasions for the years 1991-2002

x_{it} is a vector of independent observable household and individual characteristics and β is the associated vector of parameters to be estimated.

y_{it-1} is the lagged dependent variable, and allows for the presence of genuine state dependence (GSD) to be tested. It is assumed to follow a first-order Markov process. [29] If $\gamma > 0$, other things held constant, there is a dynamic causal effect of poverty in the previous period on poverty risk in the current period and thus, a state dependence effect.

v_{it} is the composite error term and represents unobserved individual heterogeneity underlying poverty persistence and is decomposed into an individual-specific time invariant effect, α_i, and a time-varying random error term, u_{it}. v_{it} is correlated over time due to the individual-specific time invariant component. Both terms are assumed to be independent of each other, normally distributed, and serially independent.

The relative importance of the unobserved effect in the total error variance of the poverty status equation is measured by ρ:

$$\rho = Corr(v_{it}, v_{is})\frac{\sigma_a^2}{\sigma_a^2 + \sigma_u^2} \qquad t, s+2,...,T \qquad t \neq s \qquad (4)$$

[29] The total number of observations per individual is T_i-1 due to the lagged dependent variable.

ρ measures the proportion of the total variance contributed by the individual level variance component. $\rho=0$ is a test of the hypothesis that that there are no unobservable characteristics in the sample, therefore, the model reduces to a simple pooled probit where no account is taken of the individual-specific unobserved differences. Thus, it ignores the cross-correlation between the composite error terms (v_{it}) across different time periods for the same individual and treats individuals that are observed at multiple time points as if they are observations on different individuals.

Two limitations of the random effects specification is that of correlated individual effects and the 'initial conditions' problem, which are now discussed along with solutions.

i. Correlated individual effects

Equation (1) assumes α_i is uncorrelated with the exogenous variables. In practice, both factors are likely to be correlated over time through the inclusion of the lagged dependent variable or through time-varying covariates. For example, intelligence may be correlated with observed education status, and an individual's motivation may be related to employment status. To allow for the possibility of correlated individual effects, this study follows the approach of Wooldridge (2005) by assuming that the individual specific effect, α_i, can be expressed as a regression function which is linear in the means of all time-varying covariates :

$$\alpha_i = \alpha_0 + \alpha_1 \bar{x}_i + a_i \qquad (5)$$

where a_i and $\bar{x}_i$ represent unobserved individual heterogeneity.

More specifically, $\bar{x}_i = \frac{1}{T}\sum_{t=1}^{T} x_{it}$ and is the temporal average of time-varying covariates for individual i and is the part of unobserved individual heterogeneity correlated with the explanatory variables. It is assumed that $a_i \sim N(0,\sigma_a^2)$ and is now uncorrelated with the x_{it} as in equation (1). The coefficients in α_1 are set equal to zero for time-invariant variables.

ii. The problem of 'initial conditions'

A second issue that needs to be resolved is endogeneity of 'initial conditions'. This problem arises because the start of the observation period does not necessarily coincide with the start of the poverty process (Arellano and Honore, 2001; Wooldridge, 2005; Arulampalam, Booth and Taylor, 2000; Stewart, 2007). A large proportion of children in the sample was not observed from birth and, therefore, was at risk of poverty before entering the sample. A child who is observed as poor at the start of the observation period may be so because of an earlier history of poverty (state dependence) or because of unobserved characteristics.

A simple approach would be to assume that the initial conditions are exogenous. This is a very strong assumption and is only likely to hold if the errors generating the process are serially independent or if the first observation for every child is the true beginning of the stochastic process. Alternatively, it could be assumed that the stochastic process that generates the observed poverty sequence is in equilibrium at the beginning of the sample period. Chay and Hyslop (2000) argue that this assumption is unlikely to hold when time-varying covariates are included as important determinants in the model. If the initial conditions are correlated with α_i, the estimator will be inconsistent and overestimate the magnitude of state dependence.

Heckman (1981) proposed a solution to the initial conditions problem by specifying a separate linear reduced form equation for the first observation of the dependent variable, y_{i1}, given the unobserved individual specific effect and observed individual characteristics:

$$y_{i1} = x_{i1}\beta + \theta\alpha_i + u_{i1} \qquad (6)$$

where x_{i1} is a vector of exogenous variables relevant at the initial period, pre-sample information that could affect the probability of poverty at t=1, and the vector of covariate means $\bar{x}_i$, which is included to pick up correlated effects between the time-varying covariates and unobserved heterogeneity. Combining equations (1) and (6) specifies a complete model for the dynamic process of poverty.

Wooldridge (2005) gives a simple alternative to the Heckman's estimator by proposing a Conditional Maximum Likelihood (CML) estimator for dealing with the initial conditions problem. This models the distribution of the unobserved effect conditional on the initial value of the dependent variable and any exogenous explanatory variables. The main advantage of the Wooldridge approach over the Heckman approach is computational simplicity as the random effects model can be estimated using routines in existing software (for example, the 'xtprobit' command in Stata). For this reason, the Wooldridge estimator is applied in this study. This approach results in a likelihood function based on the joint distribution of the observations conditional on the initial observations. Incorporating equation (5), the distribution of the unobserved effect is expressed as the Wooldridge estimator:

$$\alpha_i = \alpha_0 + \alpha_1 y_{i0} + \overline{x}_i \alpha_2 + a_i \tag{7}$$

The estimate of α_1 shows the direction of the relationship between the initial value of poverty status and the unobserved effect.

Substituting the Wooldridge estimator (7) into the dynamic random effects model (equation (1)) yields the final dynamic random effects specification:

$$y_{it} = x_{it}\beta + \gamma y_{it-1} + \alpha_0 + \alpha_1 y_{i0} + \overline{x}_i \alpha_2 + a_i + u_{it} \qquad i=1,\dots,N;\ t=2,\dots,T;\ u_{it} \sim \mathrm{N}(0,1) \tag{8}$$

Equation (8) is identical in structure to a standard random effects probit model (1), except that the explanatory variables include the initial poverty status and time averages of time varying explanatory variables to control for initial conditions and unobserved heterogeneity.

6.3.2 Average Partial Effects

The scaling of the probit coefficients is arbitrary, thus, the magnitude of the effects of the covariates cannot be directly inferred from the estimated model. An advantage of the Wooldridge estimator is that average partial effects (APEs) can be estimated. APEs show the impact of a change in an explanatory variable on the risk of experiencing poverty, averaged over the population distribution of observed and unobserved heterogeneity. These are computed by averaging the individual marginal effects over the sample (Wooldridge, 2005). The individual marginal effect of a variable is the predicted change in probability arising from a one unit increase in a particular variable, with all other variables are held at their observed values. Thus, the Wooldridge estimator allows one to not only to determine whether true state dependence exists by referring to the significance level of the coefficient of the lagged dependent variable, but also to derive the importance of this phenomenon as APEs are measured in units of probability.

To derive the APE for the presence of state dependence in poverty, predicted probabilities are calculated for each individual, *i,* conditional first on poverty in the previous period ($y_{it-1} = 1$) and secondly on non-poverty in the previous period ($y_{it-1} = 0$). The difference between these two quantities averaged over the sample gives an estimate of state dependence:

$$APE = \hat{p}_1 - \hat{p}_0 \tag{9}$$

$$\hat{p}_1 = \frac{1}{N}\sum_{i=1}^{N}\Phi(x_{it}\hat{\beta}_a + \hat{\gamma}_a y_{it-1} + \hat{\alpha}_{a0} + \hat{\alpha}_{a1} y_{i0} + \overline{x}_i \hat{\alpha}_{a2}) \tag{10}$$

$$\hat{p}_0 = \frac{1}{N}\sum_{i=1}^{N}\Phi(x_{it}\hat{\beta}_a + \hat{\alpha}_{a0} + \hat{\alpha}_{a1} y_{i0} + \overline{x}_i \hat{\alpha}_{a2}) \tag{11}$$

where the a subscript indicates multiplication by $\sqrt{1-\rho}$ (see footnote 33 for an explanation of this scaling factor). Φ is the cumulative standard normal distribution function and N is sample size. Analogously, the APE for the effect of an explanatory variable x_j on the probability of poverty is calculated by first predicting the probability of poverty at the observed values of each of the variables while the relevant dummy variable is set to zero ($x_j = 0$) and then predicting the probability of poverty with the dummy variable evaluated at one ($x_j = 1$). The difference of these expressions is then averaged over N individuals to give the APE of the variable.

6.4 Hypotheses

This chapter aims to test the hypothesis that there are three mechanisms associated with the risk of poverty persistence: genuine state dependence, unobserved and observed heterogeneity. Section 2.5 discussed the dynamic theories of poverty. Given that multiple regression models of poverty are estimated, it also aims to test whether poverty has become more democratised in society (i.e., poverty is experienced more widely in society, thus, even those with beneficial characteristics, such as education and workers in the household are not immune from it) or whether the poor are a distinct group of people from non-poor and are characterised by multiple adverse characteristics as predicted by the theories of persistent poverty.

i. **The presence of unobserved heterogeneity is associated with state dependence in poverty.**

The null hypothesis that ρ =0 is a test that there is no unobservable heterogeneity in the sample. To recall, ρ (equation 4) measures the relative importance of the unobserved effect in the total error variance from the dynamic random effects probit model. The test is established using a likelihood ratio test. If the hypothesis is not rejected, the dynamic random effects probit model is equivalent to a simple pooled probit where no account is taken of the individual-specific unobserved differences.

ii. **Experience of poverty at *t-1* increases the risk of poverty at *t*, controlling for observed and unobserved individual heterogeneity. Thus, there is genuine state dependence in poverty.**

The dynamic random effects model includes the lagged dependent variable y_{it-1} as a regressor to allow for presence of state dependence. $\gamma = 0$ is a test of the null hypothesis that lagged poverty status has no effect on current poverty status. If the null hypothesis is not rejected, the dynamic random effects model is the equivalent a static panel model for poverty. As discussed in Section 6.3.2, the magnitude of state dependence will be assessed from the average partial effect of lagged poverty status.

iii. **The risk of poverty is associated with the presence of observed heterogeneity.**

This will be judged from the statistical significance of the β coefficients and magnitude of the APEs for the independent observable household and individual characteristics.

iv. **Persistent poverty versus democratization of poverty**

This is evaluated in two main ways. Firstly, predicted probability profiles for an accumulation of 'positive' and 'adverse' characteristics are simulated and compared using parameter estimates from the dynamic random effects model. This will show how the risk of poverty is associated with various personal and household characteristics. Whilst the predicted probability of poverty is expected to increase with an accumulation of adverse risk factors, it important to ascertain how widespread this phenomenon actually is by looking at the incidence of multiple disadvantage. This is ascertained by constructing a simple index which sums the number of 'positive' and 'adverse' characteristics among the poor.

If the poor are distinct in characteristics from the non-poor, it is expected that the proportion of poor individuals is positively related to an increase in the value of 'adverse' index and negatively related to the 'advantaged' index. If the theory of democratization holds, it is expected that both indices are less skewed towards the tails of the distributions and that poor individuals have a combination of both types of characteristics.

6.5 Empirical results

The empirical results are presented in four parts. The first part presents descriptive analyses on the characteristics of poverty entry and persistence. The second part tests the hypotheses of unobserved heterogeneity, state dependence, exogeneity of initial conditions and observed heterogeneity using estimates from the regression anlyses. The importance of state dependence relative to individual heterogeneity is assessed in part three. The final part examines the relationship between cumulative disadvantage and poverty persistence through predicted probability profiles.

6.5.1 Descriptive analysis

This section explores the associations between poverty mobility and various socio-economic correlates in order to ascertain which sub-groups of individuals stay poor or enter poverty, and how these differences vary between children and all individuals. Figures 6.2 and 6.3 compare the sub-group differences in persistence and entry for children and the population, respectively.

On average, 65 per cent of children who were poor at *t* were poor the following year. This is 6.5 times the risk of poverty entry (10 per cent).[30] The general population has a similar risk of persistence as children (62 per cent) but a lower risk of entry (8 per cent). Whilst this suggests that poverty in one year causes poverty in future years, the explanatory significance of this may be limited as people experiencing similar poverty dynamics over time share particular demographic and socio-economic traits. It is likely that these also increase the risk of persistence or entry into poverty than just past experiences of poverty. This is evident from Figure 6.2 and 6.3 which describe the characteristics of individuals who were poor and non-poor in the previous year averaged over twelve years, respectively.

As expected, a number of gradients in the relationship between poverty mobility and socio-economic characteristics are evident: the risk of persistence and entry increases with a greater number of children, fewer paid workers, lower qualifications, living in rented compared to owned accommodation, and for younger heads.

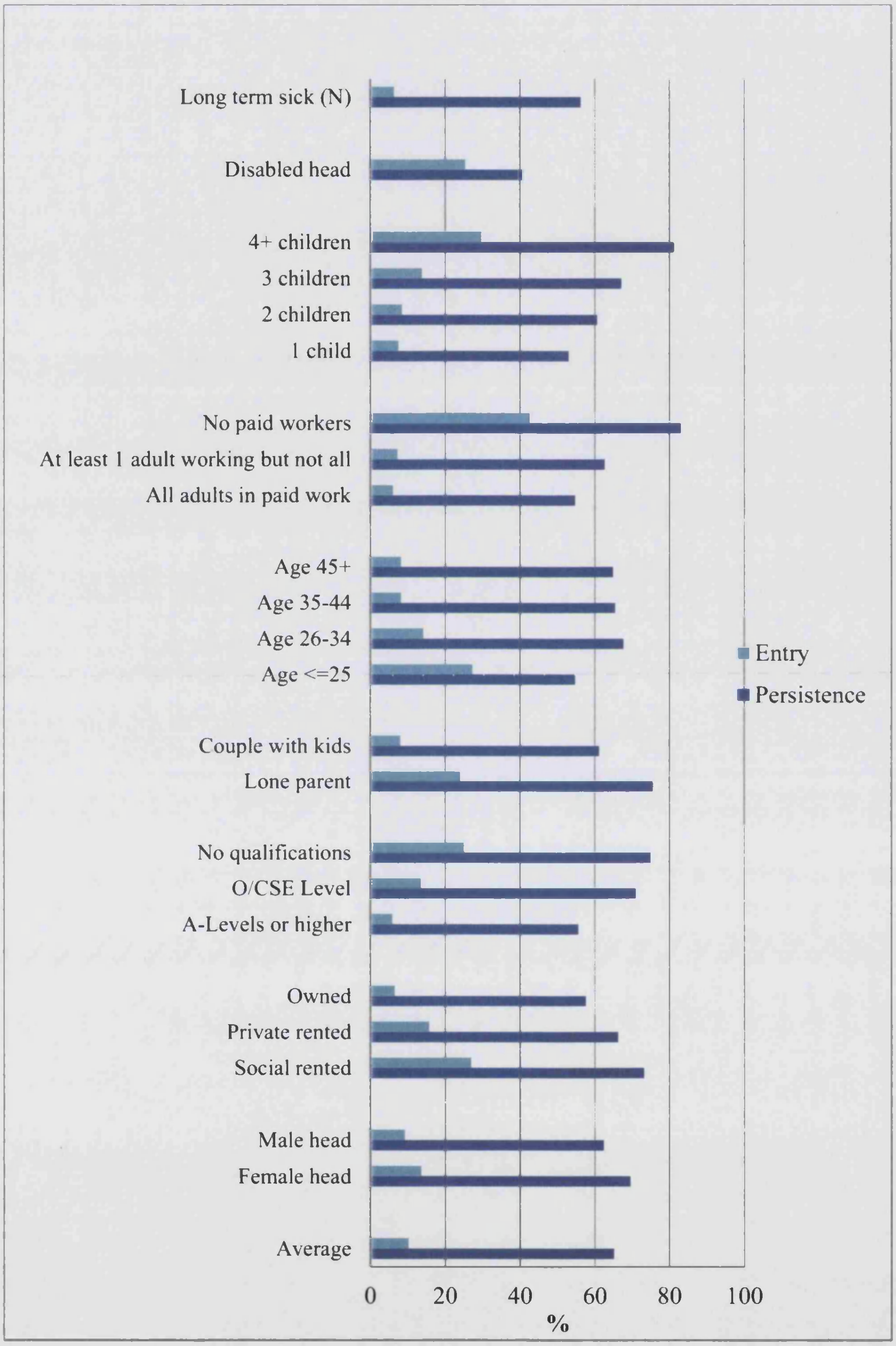
Worklessness and the presence of 3+ siblings are the two biggest risk factors for both persistence and entry. Figure 6.2 shows that 83 per cent of children from workless households are persistently poor compared with 13 per cent of those from households where all adults are in paid work. They are also disproportionately more likely to belong to workless households than all individuals (73 per cent). Furthermore, children with three or more siblings are approximately 1.5 times more likely to be persistently poor and 4 times more likely to enter poverty at $t+1$ than children with no siblings. Lone parenthood, no qualifications and living in social rented accommodation also have relatively large associations with persistence and entry. Factors that are associated with a less than average risk of persistence or entry include living in a household that is owned, with no siblings, one or more workers,

[30] Poverty entry is relatively less than persistence as the proportion of non-poor individuals is larger than the proportion of poor in any given year.

and a head with at least A-Level qualifications. Children who belong to a household head who is under the age of 25 (27 per cent) is over twice as likely to enter poverty compared with all individuals.

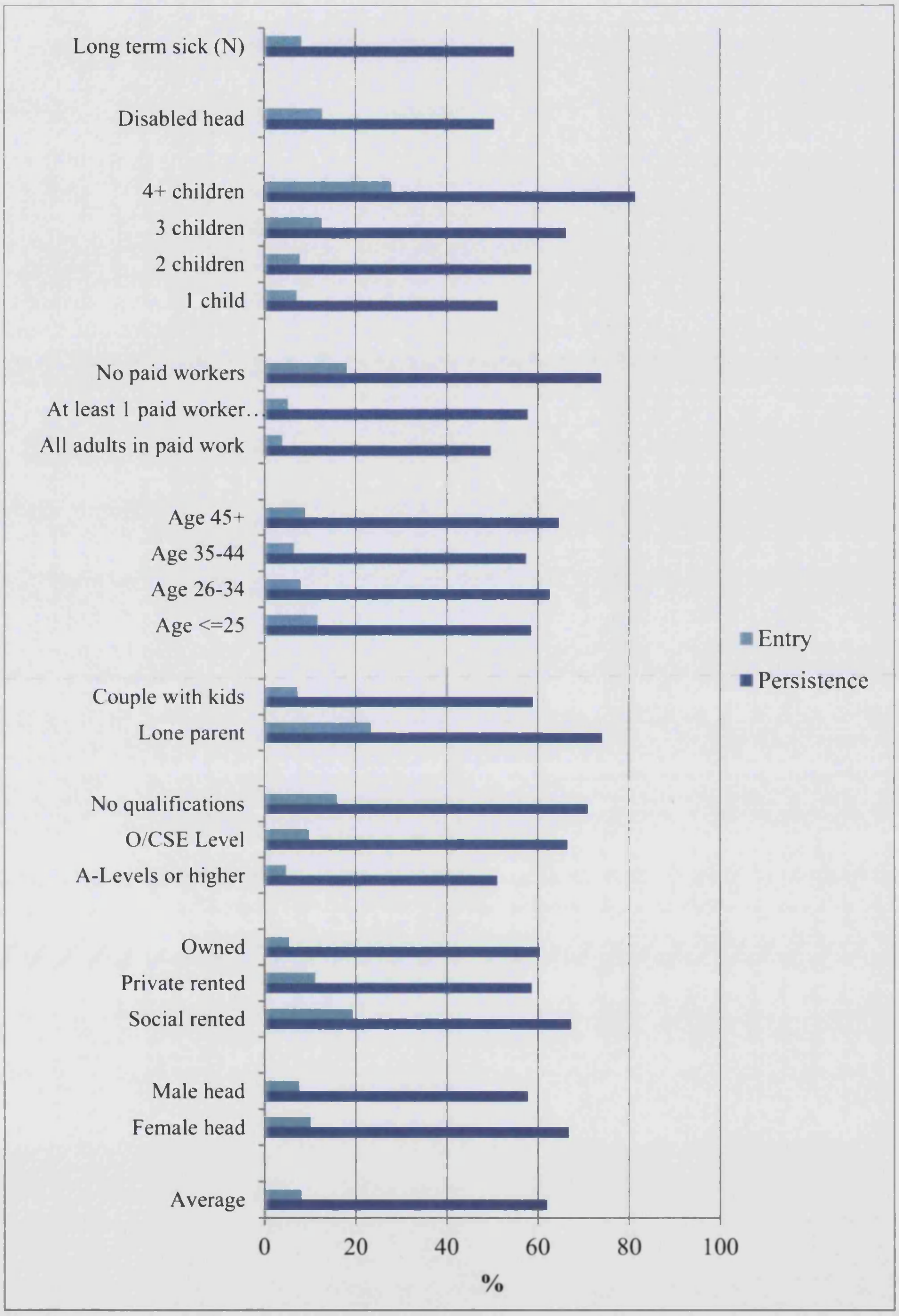
Whilst most of these findings are expected and in line with previous research, a striking finding is the relatively high proportion of persistently poor children from 'advantaged' groups such as those with all adults in employment, heads with A-Levels or higher qualifications, and owned accommodation. This points to a 'democratisation' of poverty, in that poverty is not only confined to traditional sub-groups.
These findings highlight that differences in observed heterogeneity are associated with differences in poverty mobility probabilities. The next section aims to disentangle the independent effects of state dependence, observed and unobserved heterogeneity on the probability of poverty using multiple regression.

Figure 6.2: Characteristics of poverty persistence and entry: children, 1991-2002



Source: Derived from the BHPS 1991-2002, unbalanced panel.
Persistent poor = $Pr(Poor_{t+1} \mid Poor_t)$; Poverty entry = $Pr(Poor_{t+1} \mid Not\text{-}poor_t)$
Pooled transitions between two consecutive waves.

Figure 6.3: Characteristics of poverty persistence and entry: population, 1991-2002



Source: Derived from the BHPS 1991-2002, unbalanced panel.
Persistent poor = $Pr(Poor_{t+1} \mid Poor_t)$; Poverty entry = $Pr(Poor_{t+1} \mid Not\text{-}poor_t)$
Pooled transitions between two consecutive waves.

6.5.2 Regression analysis results

This section presents the results from the regression analysis. The estimates are presented for three specifications. Firstly, a static pooled model is estimated. This does not include lagged poverty status as an independent variable, and treats each sample as a large cross-section and, therefore, assumes that the errors are independent over time and uncorrelated with the explanatory variables. This model provides baseline estimates with which results from models that include state dependence and unobserved heterogeneity can be compared. Secondly, a dynamic pooled probit model is estimated, which introduces state dependence through the inclusion of lagged poverty status. [31] Finally, the dynamic random effects model is estimated, which accounts for both unobserved heterogeneity and state dependence, and controls for initial conditions and correlated effects using the Wooldridge estimator. [32] These results are all presented as parameter coefficients[33], but the main results are later discussed in terms of percentage points via estimation of average partial effects. [34]

Tables A6.1 and A6.2 in the Appendix present the coefficient estimates for the probit models using the unbalanced and balanced samples for the whole population and children, respectively. Both samples are analysed to gauge the robustness of the coefficients due to sample attrition. The results are discussed in four steps: i) unobserved heterogeneity, ii) state dependence, iii) exogeneity of the initial conditions, and iv) observed individual heterogeneity.

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[31] Robust standard errors are used to account for serial correlation in the errors at the individual level.

[32] The reported random-effects probit estimates were obtained by employing the adaptive Gauss-Hermite quadrature method in Stata 9.1 to compute the log likelihood and its integral. The models were estimated by increasing the number of quadrature points to 30 by using the 'quadchk' command. Specifically, the use of 24 quadrature points produced coefficient estimates that did not change much with the addition of further quadrature points (most coefficients change by less than 0.01% and none change by more than 1%). The estimated results, therefore, are sufficiently accurate and can be interpreted with confidence.

[33] Comparisons of pooled probit estimates with those from a random effects probit model need to account for the different normalisations implemented by commercially available software (Arulampalam, 1999). In the random effects model, the normalization is based on the random error term u_{it} with the individual-specific effect estimated separately via α_i in the composite error term (v_{it}). In the pooled probit model, the unobservable individual effect is still part of the error term on which the normalization is based, i.e., v_{it} takes no account of individuals being observed more than once. In order to compare the estimated coefficients from both specifications, the random effects estimates need to be rescaled by multiplying the coefficients by a factor of:

$$\frac{\sigma_u}{\sigma_v} = \sqrt{1-\rho} \quad \text{where } \rho = \frac{\sigma_a^2}{\sigma_a^2 + \sigma_u^2}$$

For consistency, the average partial effects are also computed using the scaled coefficients.

i. **Hypothesis i: The presence of unobserved heterogeneity is associated with state dependency in poverty**

The first source of poverty persistence to be considered is unobserved individual heterogeneity. Model 2 explicitly introduces this into the dynamic models by specifying random effects. Allowing for unobserved heterogeneity improves the fit of the models compared with the pooled probit models as shown by the improvement in the log-likelihood. The likelihood ratio test of the null hypothesis that $\rho=0$ is rejected at the 1% level of significance. The estimates of ρ are similar for the unbalanced and balanced samples and for the whole population and children, and across the poverty lines (Table 6.2). Approximately 40% of the share of total error variation in the data is attributed to unobserved individual heterogeneity.

Table 6.2: Summary of unobserved heterogeneity across poverty lines

		Population		Children	
		Unbalanced	**Balanced**	**Unbalanced**	**Balanced**
50% PL	ρ (s.e.)	0.382 (0.009)	0.392 (0.012)	0.370 (0.016)	0.370 (0.033)
	Test statistic for H0: $\rho=0$	1111.66***	721.01***	303.33***	88.17***
60% PL	ρ (s.e.)	0.404 (0.009)	0.419 (0.032)	0.386 (0.017)	0.362 (0.032)
	Test statistic for H0: $\rho=0$	2006.44***	1202.06***	405.88***	98.72***
70% PL	ρ (s.e.)	0.411 (0.009)	0.427 (0.012)	0.412 (0.016)	0.423 (0.032)
	Test statistic for H0: $\rho=0$	2063.81***	1483.99***	569.80***	203.32***

Source: Derived from the BHPS 1991-2002. * $p<0.10$ **$p<0.05$ ***$p<0.01$

ii. **Hypothesis ii: Experience of poverty at *t-1* increases the risk of poverty at *t*, controlling for observed and unobserved individual heterogeneity.**

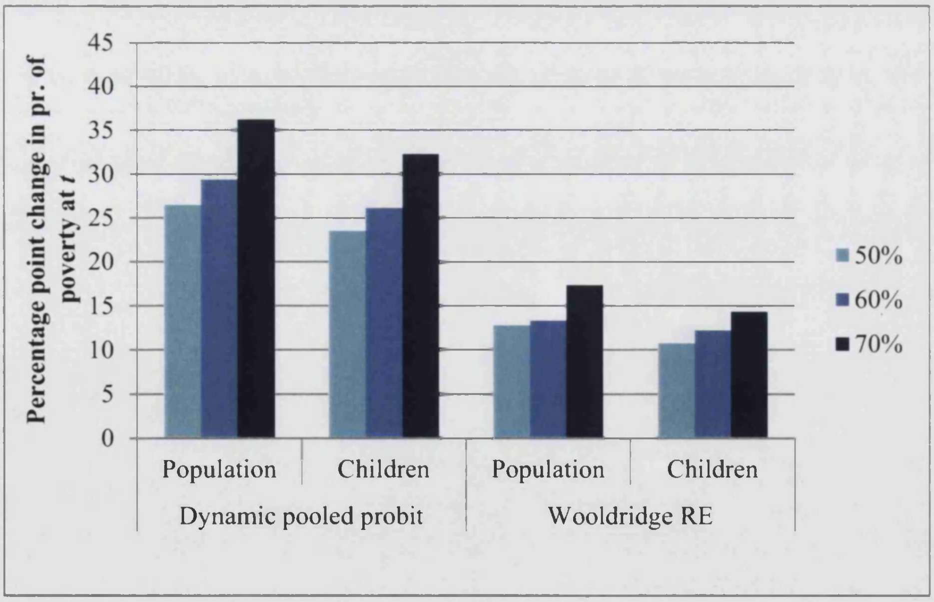
The second source of persistence is genuine state dependence. The coefficient on lagged poverty status in the dynamic models is included as an indicator of this (models 2 and 3 in tables A6.1 and A6.2). This variable enters all of the estimated models for both samples with statistically strong effects and is large compared with other coefficients. This suggests that even after controlling for observed and unobserved differences, poverty in the previous year is associated with an increased risk of poverty in the current year. This finding is robust across all three poverty line thresholds.

[34] Both of the dynamic specifications contain year dummies to capture any annual effects.

The size of the genuine state dependence effect is presented as average partial effects. Tables A6.3 and A6.4 present the APEs for the 50 per cent poverty line for the population and children, respectively. Tables A6.5 and A6.6 give estimates for the 60 per cent threshold, and tables A6.7 and A6.8 for the 70 per cent threshold for both samples. The estimates confirm the pattern from the descriptive analysis that children have a similar risk of poverty persistence as the general population. Controlling for unobserved heterogeneity reduces the explanatory magnitude of state dependence: in the dynamic pooled specifications, the probability of current poverty for an individual who was poor in the previous year is approximately 30 percentage points higher compared with an individual who was previously non-poor. However, when unobserved heterogeneity is introduced in the Wooldridge random effects specification, state dependence is reduced by almost a half to 13 percentage points for both the population and children (Table A6.5 and A6.6).

Figure 6.4 compares the APEs for the lagged poverty status regressor across all three poverty lines. As expected, the size of the coefficient increases with the poverty line thresholds as the proportion of poor people increases. Children have a slightly lower risk of state dependence relative to the general population. Unobserved heterogeneity attenuates the effect of state dependence, with a robust finding being that the pooled probit estimates are double those of the random effects estimates.

Figure 6.4: Comparison of lagged poverty status across poverty lines (APEs)



Source: Derived from the BHPS 1991-2002, unbalanced panel.
Estimates derived from average partial effects controlling for other factors (tables A6.3 to A6.8)

iii. Exogeneity of initial conditions

Exogeneity of the initial conditions is established by testing the null hypothesis that poverty status in the initial time period is equal to zero. It is evident from models 2 and 3 that exogeneity is strongly rejected at the 1 per cent level for both the whole population and children (tables A6.1 and A6.2). This finding is robust to poverty line specification. The estimated coefficients on the initial period observations for poverty status are all positive, implying a positive correlation between the initial period observations and unobservable characteristics. These findings concur with those of Capellari and Jenkins (2002, 2004) and Poggi (2007).

iv. Hypothesis iii: The risk of poverty is associated with the presence of observed heterogeneity

This section discusses the impact of the explanatory variables on poverty in terms average partial effects of a change in each explanatory variable on the probability of poverty and are expressed as percentage point changes.

Before discussing the findings in more detail, robustness of the estimates across the balanced and unbalanced samples is assessed. For the children's sample (tables A6.4, A6.6, and A6.8), APEs from the unbalanced panels tend to be smaller than those from the balanced panel, whereas in the population models (tables A6.3, A6.5, and A6.7), they tend to be of a similar size across both specifications. This is likely to be because the population sample is larger than the children's sample and suffers from lower attrition bias. In both samples, age of the head, the number of children, disability status of the head, and the number of long-term sick are not stable across the different probit specifications, as evidenced by the changes in the size and significance of the coefficients.

In the static pooled probit models (columns 1 and 2, tables A6.3-A6.8), the signs of the coefficients are as expected from the descriptive analysis and consistent with the corresponding patterns in the dynamic models. However, the inclusion of state dependence, initial conditions, and unobserved heterogeneity tends to attenuate the effects of observed heterogeneity, as shown by the smaller estimates in both of the dynamic models compared to the static pooled model.

The estimates from the dynamic pooled and random effects models (columns 3-6, tables A6.3-A6.8) are, in general, similar and there are no instances in which significant covariates change sign or differ dramatically in their magnitude for both samples. The inclusion of unobserved heterogeneity mainly affects state dependence, as discussed earlier, but does not otherwise significantly alter the estimated impact of the personal and household covariates. As such, the model comparisons act more as a robustness check on the estimated results and to ascertain the impact of state dependence and unobserved heterogeneity, without the need to choose between competing sets of estimates. For simplicity, results are discussed in the context of the Wooldridge model estimates and primarily with respect to the 60 per cent poverty line (columns 5 and 6 of tables A6.5 (population) and A6.6 (children)), but comment is also provided on the sensitivity to alternative thresholds.

The biggest factor affecting the probability of poverty relative to all other socio-economic characteristics is a lack of employment in the household. For both samples, living in a workless household increases the risk of poverty by approximately one-fifth compared with households where all adults are in paid work. Having at least one paid worker also significantly increases the risk of poverty although the effect is relatively small. This finding highlights that paid work itself is not enough to avoid poverty.

The number of children in the household has a positive and quantitatively strong impact on the risk of poverty. These effects are statistically significant in all models and for both samples. Having at least three siblings increases the probability of poverty for children by 12-18 percentage points. This is approximately three times the effect for children with one sibling (4-7 percentage points). The corresponding figures for the population are similar. The presence of children could increase the risk of poverty because they usually do not earn income but are consumers, thus, income reduces with each additional child. Furthermore, many people tend to have children before their working career has stabilised and before their earning power has reached its peak.

Categories for education status enter all models with positive and significant effects for both the population and children. Thus, individuals belonging to households whose heads have O/CSE level or no qualifications are more likely to be poor than those with at least A-Level qualifications. More highly educated individuals are likely to have access to a wider variety of better paid job opportunities than less educated individuals, and are less likely to be unemployed. Once state dependence, initial conditions and unobserved heterogeneity have been controlled for, the effects of education status become smaller and the gradient between both categories is less apparent than in the simple static pooled specification. A comparison of the APEs shows that education status of the head has a greater effect on the probability of poverty for children compared to the population: O/CSE level qualifications increases the probability of poverty for a child by 2.5-2.6 percentage points compared to 1.4 percentage points for the population.

Individuals from female headed households have significantly higher risks of poverty than those from male headed households, with the risk being greater for children (1.17-2.85 percentage points) compared with all individuals (0.77-0.92).

Residing in rented accommodation is associated with higher risks of poverty than living in privately owned accommodation, with the effects being larger for social renters than private renters. This is expected since owner-occupation is associated with long-term financial commitment that may encourage individuals to retain employment. Furthermore, owner occupation may measure accumulated wealth. Children living in social rented housing are disproportionately more likely to be poor than the population (7-12 percentage points versus 4-5 percentage points, respectively). Living in private rented accommodation is insignificantly different to living in owned accommodation for children in the dynamic models.

In the case of family composition, lone parenthood is statistically significant and associated with an increased risk of poverty across all specifications. With regards to the general population, it is the only category with a positive sign. Individuals from couple families are less likely to be poor than those from single childless households. The size of the effect, however, is smaller for couples with children than couples without children. For children, lone parenthood is one of the largest risk factors affecting poverty status relative to other characteristics and increases the probability by 9-12 percentage points. The effects of family composition on poverty are likely to be mediated through employment rather than the presence of children per se. For example, the greater caring and rearing responsibilities of lone parents could reduce the amount of time in employment, causing lower income, whereas there are potentially two earners in couple families.

The effect of the age of the head on the probability of poverty is unstable and largely insignificant, particularly in the children's sample. In the population models, there is evidence in the static specification that heads who are aged 35-44 are significantly less likely to be poor than heads who are under 25 years of age, which reflects upward mobility in the head's career.

Disability status of the head does not appear to be a significant predictor of child poverty but is negatively associated with poverty for the population. The number of long-term sick, is positively associated with poverty for both samples in the unbalanced Wooldridge model but the effect is small. Poor health may reduce the numbers of employed individuals in the household if it limits the type or amount of work that can be undertaken. Furthermore, employers may be less willing to hire those who are long-term sick if it affects productivity. An explanation for the weak results could be that the welfare state is effective in protecting people against the negative economic effects of ill-health and disability.

With regards to the sensitivity of the results to 50 per cent and 70 per cent median income poverty lines, there is a high level of consistency across the models in the sets of regressors that have statistically significant associations with poverty status. One notable difference relates to the sex of the household head. For both samples, the association between female headed households and poverty are significant at the 50 per cent and 60 per cent thresholds but not at 70 per cent. Also, the APEs are larger at the 50 per cent models compared to the 60 per cent models. This finding is consistent with that reported by Cappellari and Jenkins (2002) in their sensitivity analysis. Thus, individuals from female-headed households have a greater risk of poverty when the income threshold is relatively low.

In summary, the findings suggests that if unobserved factors are correlated with measured explanatory variables but are not accounted for in models of poverty dynamics, this may lead to the overestimation of true state dependence and biased coefficients.

6.5.3 The importance of genuine state dependence relative to observed and unobserved heterogeneity: A decomposition analysis

Stewart and Swaffield (1999) and Cappellari and Jenkins (2004) derive estimates for the fraction of raw data persistence that is attributable to genuine state dependence controlling for individual heterogeneity. In the language of Cappellari and Jenkins (2004), these quantities are known as aggregate state dependence and genuine state dependence. From these quantities, the proportion of raw persistence attributable to genuine state dependence and observed and unobserved heterogeneity can be derived.

i. Aggregate state dependence (ASD)

ASD is the difference in the average probability of being poor in the current year given poverty in the in the previous year $(\Pr(P_{it}=1 \mid P_{it-1}=1))$, and the average probability of being poor in the current year given non-poverty in the previous year $(\Pr(P_{it}=1 \mid P_{it-1}=0))$. They are based on raw transition probabilities that do not control for differences in observed or unobserved characteristics:

$$\text{ASD}=\left(\frac{\sum_{i\in\{P_{it-1}=1\}}\Pr(P_{it}=1 \mid P_{it-1}=1)}{\sum_i P_{it-1}}\right)-\left(\frac{\sum_{i\in\{P_{it-1}=0\}}\Pr(P_{it}=1 \mid P_{it-1}=0)}{\sum_i (1-P_{it-1})}\right) \tag{12}$$

ii. Fraction of ASD attributable to genuine state dependence (GSD)

GSD is derived from the average partial effect of the lag poverty status regressor from the dynamic random effects (DRE) model, and thus, incorporates the effects of observed and unobserved heterogeneity. It is calculated using Equation 9. GSD as a proportion of raw data persistence is given by:

$$\frac{GSD_{DRE}}{ASD} \tag{13}$$

iii. Fraction of ASD attributable to total (observed and unobserved) heterogeneity

Once the proportion of GSD has been derived, the remaining proportion of ASD is due to total heterogeneity and is be calculated as:

$$1-\frac{GSD_{DRE}}{ASD} \tag{14}$$

The final two quantities show how total heterogeneity is decomposed into observed and unobserved heterogeneity.

iv. Fraction of ASD attributable to observed heterogeneity

In order to derive this quantity, it is necessary to refer to the dynamic pooled probit (DPP) model as this controls for state dependence and observed heterogeneity only. It is calculated as:

$$1-\frac{GSD_{DPP}}{ASD} \tag{15}$$

v. Fraction of ASD attributable to unobserved heterogeneity

Finally, the fraction of ASD arising from unobserved heterogeneity is given by the difference of total and observed heterogeneity:

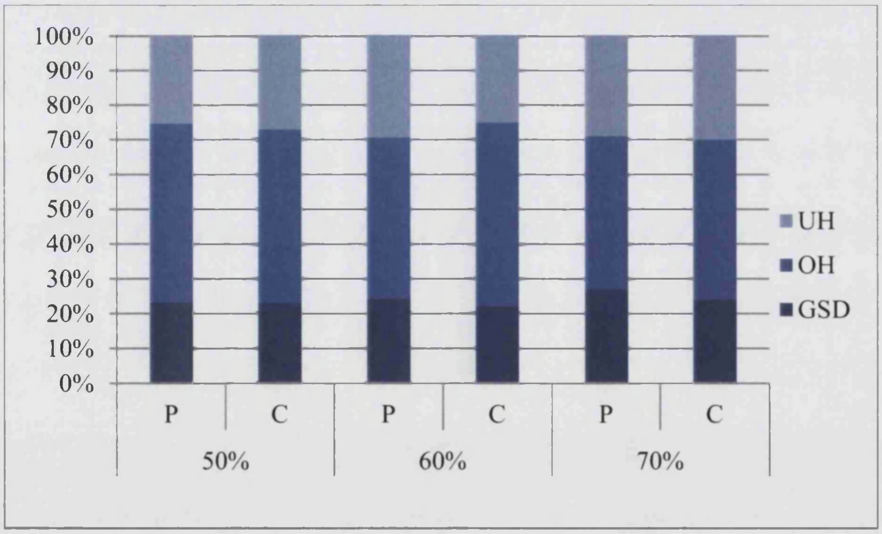
$$\left(1-\frac{GSD_{DRE}}{ASD}\right)-\left(1-\frac{GSD_{DPP}}{ASD}\right) \tag{16}$$

These quantities are presented in Table A6.9 in the Appendix. To check for robustness, they are calculated using the balanced and unbalanced samples and for various poverty lines. On the whole, estimates of the share of raw state dependence that is attributable to genuine state dependence and individual heterogeneity are robust to attrition and the definition of the poverty line (Figure 6.5). One noticeable difference is that the share of observed heterogeneity tends to be larger in the unbalanced sample due the presence of a greater number of cases. Furthermore, the children's estimates are close to those of the general population.

At the 60 per cent poverty line, the measure of raw state dependence, ASD, is estimated to be 0.55 for both samples, whereas genuine state dependence (GSD) is estimated to be about 0.13. Accordingly, a quarter of raw persistence can be attributed to genuine state dependence and three-quarters to total heterogeneity. Observed heterogeneity constitutes around half the share of raw persistence (children: 53 per cent; population: 46 per cent). The remainder is attributable to unobserved heterogeneity (children: 25 per cent; population: 29 per cent).

Cappellari and Jenkins (2004) estimate ASD in Britain to be 0.53 and GSD to 0.31 when using a poverty line set at 60 percent of median income. Accordingly, about 59 percent of poverty persistence is estimated to be due to state dependence and 41 percent due to total heterogeneity. Possible reasons as to why the estimates for GSD in the current study are lower than that of the Cappellari and Jenkins are that the latter study utilizes only 9 waves of the BHPS and the sample is comprised of adults aged 20-59 only.

Figure 6.5: Composition of Aggregate State Dependence



Source: Derived from the BHPS 1991-2002.
UH=unobserved heterogeneity; OH= observed heterogeneity; GSD=genuine state dependence.
P=general population; C=children

The significant coefficients on lag poverty status and the relatively high proportion of raw state dependence accounted for by genuine state dependence indicate that previous experiences of poverty contribute to persistence. However, the largest share of poverty persistence is attributable to observed heterogeneity.

6.5.4 Predictions - Hypothesis iv: democratisation of poverty versus persistent poverty

The previous section uncovered how the estimated probabilities of poverty change for individuals who differ in one characteristic, whilst holding the others constant. An alternative way of exploring the effects of the determinants is to examine the differential impacts that changes in more than variable have on the predicted probability of poverty.

i. Predicted probability profiles for the risk of poverty

In this section, predicted probabilities of poverty are simulated in an attempt to draw out the implications for poverty experiences under different scenarios. The coefficients from the regression analysis provide limited information in terms of understanding the scale of association between poverty and the predictors in the analysis. It possible to assess the impact of belonging to a particular group by estimating the probability of being poor at specified values of the characteristics. Predicted probabilities are, therefore, useful as they show the size of an effect rather than just the statistical significance.

The reference case consists of an individual from a couple family with two children (or one sibling in the case of children) who lives in owned accommodation, with all adults in paid work, and no disabled or long-term sick adults. Furthermore, the household head is male, aged 26-34 and has at least A-Level qualifications. A sensitivity analysis is then conducted by changing each characteristic one at a time. Clearly, this does not reflect reality as socio-economic conditions are not static. Multiple factors contribute towards a particular poverty experience, and changing a single factor may not lead to a large change in the probability of poverty for an individual. For example, higher education levels without the accompanying employment opportunities will do little to alleviate poverty. To overcome this limitation and to highlight the cumulative impact of 'disadvantage' on poverty, predicted probabilities are also simulated by concurrently changing all of the characteristics. The various predictions were derived using the point estimates of the parameters from the unbalanced RE models (60 per cent of median income poverty line). The results are presented in Figure 6.6.

Figure 6.6: Predicted probability of poverty at *t*

Reference person 1

'Advantaged'

Not poor at *t-1*	Male	Private owned	At least A-Levels	Couple	Aged 26-34	All employed	2 children	Not disabled	No long-term sick

Pr($Poor_t$) with all 10 characteristics

Population: 0.028 Children: 0.017

Change in each characteristic (ceteris paribus)

Sample	Poor at *t-1*	Female	Social rented	No qualifications	Lone	Aged <=25	Workless	4+ children	Disabled	2 long-term sick
Population	0.120	0.130	0.182	0.138	0.248	0.127	0.460	0.274	0.104	0.142
Children	0.071	0.082	0.136	0.087	0.203	0.076	0.307	0.132	0.092	0.099

Reference person 2: 'Disadvantaged'

	Population	Children
Pr($Poor_t$) with all 10 characteristics	0.775	0.836
Ratio RP 2:RP 1	27.99	49.58

Source: Derived from the BHPS 1991-2002.

The probability of poverty for an 'advantaged' reference individual is very small, and is lower for children (0.017) compared to the population (0.028). A change in a single characteristic, however, increases this probability to at least 0.07 for children and 0.10 for the population.

For individual changes in each characteristic, children are still less likely to be poor compared to the population. Predictably, worklessness has, by far, the largest effect on the probability of poverty and increases the risk to 0.460 for the population and 0.307 for children. Lone parenthood and the number of children are also important risk factors that have large impacts on the probability of poverty.The impact of having no qualifications is not as large as the impact of other characteristics, for example, the number of long-term sick. Although this is a surprising finding, the results show that the risk of poverty is mediated through employment. An increase in the number of long-term sick people reduces the potential pool of workers through the inability to work or due to caring for the sick.

Although a change from being not-poor to poor in the previous period induces a relatively large increase in the probability of poverty (0.120 for the population and 0.071 for children), the magnitude of this effect is the smallest compared with all other characteristics. This is because 'advantaged' individuals are shielded from the effects of poverty through protective factors, primarily employment. This finding indicates that although state dependence is an important determinant of poverty, the magnitude of the effect varies according to characteristics of the household.

The effect of belonging to households with all of the adverse characteristics is very dramatic for both samples. Children not only have a higher probability of poverty than the general population (0.836 versus 0.775), the cumulative impact of the risk factors is disproportionately greater for children: a 'disadvantaged' reference child is approximately fifty times more likely to poor than an 'advantaged' counterpart. The corresponding figure for all individuals is thirty times more likely.

ii. The incidence of multiple disadvantage among the poor

Whilst the predicted probability profiles indicate the relative change in the probability of poverty given the accumulation of various factors and the stark inequality between both reference groups, it is important to gauge the *extent* of cumulative disadvantage. This is explored by creating a simple index which sums the number of 'advantaged' or 'adverse' characteristics per respondent.

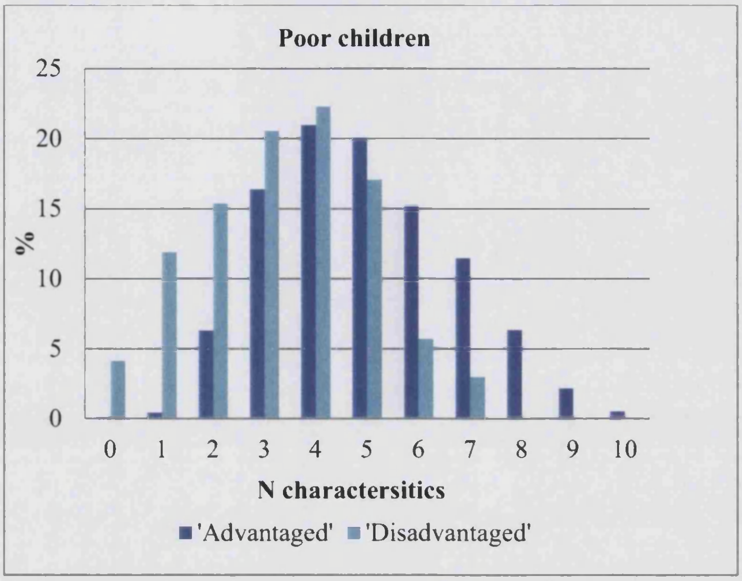
Figure 6.7 shows the distribution of the 'advantaged' and 'disadvantaged' indices amongst the samples of poor and non-poor children. If the theory of 'cumulative disadvantage' holds, it is expected that the proportion of poor children is positively related with an increase in the 'disadvantaged' index and negatively related with an increase in the 'advantaged' index. The opposite is expected in the case of non-poor children. If the theory of 'democratisation' holds, it is expected that both indices are less skewed towards the tails of the distributions and that poor and non-poor individuals have a combination of both.

With regards to the sample of poor children, the shape of the distributions for both indices is similar (contrary to expectations), with the mode being 4 charactersitics. 4 per cent of poor children have no adverse characteristics, whereas no children have all 10. There is an accumulation of risk factors but the index declines sharply after 4. Interestingly, after this point, poor children are much more likely to have 'advantaged' characteristics but before this point, they are more likely to have adverse risk factors. 40 per cent of poor children have 4 or 5 negative risk factors, however the same proportion have 4 or 5 positive characteristics.

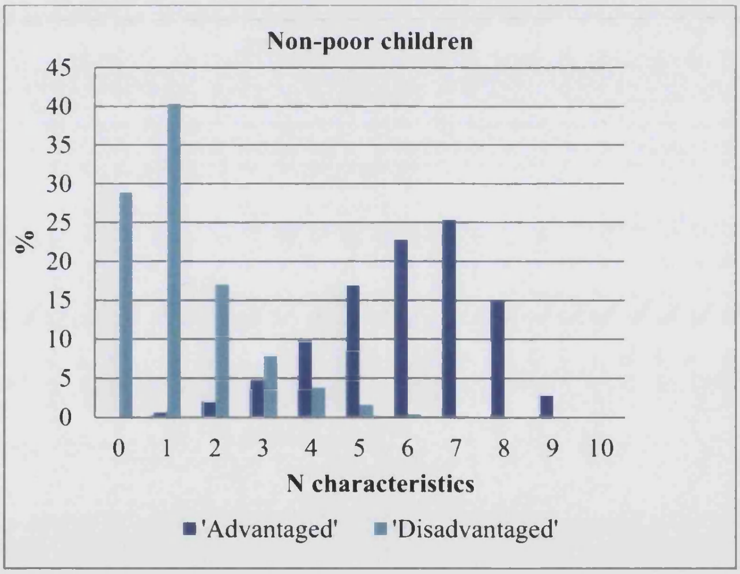
The distribution of the characteristics amongst non-poor children is distinctly different from that of poor children and in line with expectations. Nearly 30 per cent have no 'disadvantaged' characteristics. The mode is 1 characteristic (40 per cent), with a sharp decline thereafter. The distribution of the 'advantaged' characteristics is skewed towards the top end, with the mode being 7. No children have all ten factors but almost a fifth (18 per cent) have 8 or 9. Indeed, "cumulative advantage" appears to be a more distinct characterization of the non-poor.

These findings highlight that whilst the predicted probabilities show that 'cumulative disadvantage' is a potential problem amongst the poor, the incidence estimates do not provide support for this hypothesis. Instead, poverty appears to be more 'democratised', with a large proportion of poor children having several positive/protective characteristics. Layte and Whelan (2002) also find no evidence for the existence of an accumulation of disadvantage amongst the poor in their comparative study of Britain, Italy, Ireland, and Germany. Using four variables (respondent's father is unskilled manual, respondent is unskilled manual, unemployed, and poor education), the authors find that each of the factors raises the risk of poverty but with regards to the incidence of cumulative disadvantage, the authors state that, "... *long before we identify groups doomed to poverty we run out of numbers*" (p.p.223).

Figure 6.7: The distribution of characteristics across poor and non-poor children at *t*



Source: Derived from the BHPS 1991-2002.



Source: Derived from the BHPS 1991-2002.

6.6 Conclusion

The aim of this chapter was to study the correlates of poverty and, more specifically, to establish to what extent the persistence of poverty is related to true state dependence or individual heterogeneity. It did this by estimating a dynamic random effects model controlling for observed and unobserved individual heterogeneity. Two methodological issues, namely, correlated effects and initial conditions, were addressed by using the Wooldridge estimator.

The findings showed that previous poverty was a significant predictor of current poverty independent of individual observed and unobserved heterogeneity. This was robust across samples and poverty line thresholds. The decomposition analysis of aggregate state dependence showed that genuine state dependence accounted for approximately one-quarter of raw state dependence. These results suggest that early interventions could have long-lasting benefits for poor children and reduce overall child poverty by reducing the share of poverty entries and increasing the share of poverty exits.

The importance of unobserved heterogeneity was demonstrated in three ways. Firstly, approximately 40 per cent of the share of total error variation in the data was attributed to unobserved heterogeneity, and this estimate was robust across all three poverty line thresholds. Secondly, a non-trivial share of raw persistence (approximately a quarter) was accounted for by unobserved characteristics. Thirdly, the impact of state dependence and observed correlates of poverty was attenuated once unobserved heterogeneity was introduced in the models.

Observed heterogeneity accounted for the biggest share (approximately 50 per cent) of raw state dependence. This indicates that policies targeted towards worklessness, education, or support for large families could be beneficial for poverty reduction. Most the findings with regards to the observed correlates of poverty were expected and in line with previous research. Worklessness and the number of children were among the main risk factors associated with poverty. Education status of the head appeared to affect children disproportionately more than the general population. Policy interventions directly targeted at such characteristics have the potential to improve the financial well-being of children and, thus, to reduce child poverty. In the short-term, provision of childcare facilities could increase labour market participation of adults with children. Longer-term policies could improve education participation and attainment for children from disadvantaged backgrounds.

There is also evidence of substantial correlation between unobserved individual heterogeneity and initial conditions. Failing to control for unobserved heterogeneity overstates the degree of state dependence in poverty over time.

The hypotheses of a 'democratisation' of poverty versus 'cumulative disadvantage' were tested specifically by simulating various probability profiles using the coefficients from the dynamic random effects models. The predicted probabilities provided upper and lower bounds for the impact of state dependence and individual heterogeneity on child poverty. Whilst an accumulation of adverse risk factors substantially increased the risk of poverty, there was no evidence that individuals with such characteristics actually existed in the samples. Thus, there is no evidence that poverty is associated with 'cumulative disadvantage'. In fact, those who were poor had multiple favorable characteristics. Furthermore, the descriptive analysis showed that a relatively high proportion of persistently poor children were from households with all adults in employment, heads with A-Levels or higher qualifications, and owned accommodation. These findings point to a 'democratisation' of poverty. This does not mean that poverty is no longer shaped by traditional factors but that those with favourable characteristics are not immune to the experience of poverty.

In summary, the findings show that there are multiple underlying causes related to the risk of poverty. Policies aimed at eradicating child poverty need to take into account the various factors as simply raising the incomes of the poor through increases in benefits may not be effective for keeping people out of poverty over the long-term. Multiple short-term and long-term policies are required that are targeted towards vulnerable groups (such as lone parents and large families) or at specific areas (worklessness, working poor, education attainment).

A limitation of the analysis in this chapter is that it did not consider poverty dynamics beyond a first-order Markov process. The literature on spells and hazard models clearly indicates that longer-term duration dependence exists. Although for policy purposes it is important to establish the nature of poverty experiences in terms of length and spacing of the spells (for example, long spells versus short repeated spells), the presence of state dependence itself, regardless of duration, should be of policy concern due to the associated welfare costs associated with poverty (Arulampalam, 2000). The next chapter will address this limitation by exploring specific typologies of longitudinal poverty over the longer-term.

Chapter 7 Long-term Trajectories of Poverty: A Latent Class Growth Analysis

"Time is seldom taken fully into account in the definition of and measurement of poverty. This omission is important. Time is not simply a further dimension over which poverty can be measured. It is the medium within which poverty occurs and shapes the experiences of being poor."

(Walker, 1994, p.p. 11)

7.1 Introduction

The previous chapters considered poverty from a point-in-time perspective (i.e., at t) and as transitions (i.e., between t and $t+1$). It is important to understand whether and why people follow different trajectories over a longer period of time, and to identify the factors that distinguish the likelihood of following particular poverty trajectories. Experiencing poverty in any given time period may not lead to severe disadvantage if it is unlikely to be repeated again. In contrast, a lengthy period of poverty may have deleterious effects on standards of living, with particularly harsh consequences for children over the life-course. As such, this chapter progresses the analysis to consider long-term *trajectories* of poverty by utilising the entire series of poverty measurements between 1991 and 2002.

An important development in the literature on poverty dynamics has been the classification of longitudinal patterns of poverty based on the number of times that individuals are counted as poor. Much of this research has been descriptive in nature and based on subjective rules of categorisation, however, there are a number of methodological limitations attendant to this approach. Firstly, it is not possible to statistically validate whether the groups represent true variation in the population. Secondly, *within* each group, it is not possible to assess how the probability of poverty changes over time. Thirdly, the cut-off thresholds for defining group membership are arbitrary.

Following the argument that time is a significant factor for shaping the experience of being poor, and the proliferation of studies which show evidence of heterogeneous patterns of poverty over the long-term, this chapter addresses the shortcomings of the subjective categorization approach by modeling dynamics over the 1991-2002 period to ascertain whether there are a number of statistically distinct trajectories using a latent class growth analysis (LGCA) framework (Nagin, 2005; Muthen 2004). It goes on to examine the way that latent class membership is related to different covariates via multinomial logistic regression.

The remainder of the chapter proceeds as follows: Section 7.2 reviews and critiques the related literature. The modeling technique is described in 7.3. The hypotheses are set out in 7.4. The estimation results in section 7.5 are discussed in four parts: model fit, description of the shapes of the poverty trajectories, determinants of the trajectories, and simulated predicted probability profiles. The final section summarises the findings and concludes.

7.2 Previous literature

A key development in dynamic approaches to the study of poverty has been the classification of longitudinal poverty trajectories. Initial work in this area has relied upon subjective categorisation rules to create sub-groups with seemingly distinct poverty patterns. This section reviews and critiques some of the studies that have employed this method.

In their attempt to classify Income Support recipients according to the pattern of benefit receipt over time, Ashworth and Walker (1997) point out that,

> *"There are, in broad terms, two conceptual approaches to creating typologies. The first is to define groups a-priori on the basis of expected patterns of welfare receipt. The second is to allow the observed data to generate the typology based upon the judicious selection of relevant classificatory variables and the application of a suitable grouping technique."* (Ashworth and Walker, 1997, p.p. 5).

With regards to the development of typologies of poverty experiences, previous studies have tended to opt for the first approach. One of the earliest attempts was undertaken by Ashworth et al. (1994) who defined six patterns of poverty (Table 7.1) based upon the number of spells, the length of each spell and the time spent out of poverty for a sample of children living in the United States using data from the PSID.

Table 7.1: Ashworth et al.'s (1994) typology of poverty

Pattern	Definition
Never poor	Never observed as poor over the entire observation period (fifteen years)
Transient poverty	A single short spell of poverty lasting one year
Occasional	Multiple short spells of poverty lasting no more than a year each
Recurrent	Multiple spells of poverty, some separated by more than a year and some exceeding a year
Persistent	A single spell of poverty lasting between two and thirteen years
Chronic	Repeated spells of poverty never separated by more than one year of non-poverty
Permanent	Poverty lasting continuously over the entire observation period

Source: Ashworth at al. (1994)

Using simple tabulations, the authors found that each pattern occurred among American children, each group was distinguished by different levels of income, and each group was associated with distinct socio-demographic characteristics. Subsequent studies have developed their own taxonomy. Using BHPS data, Muffels et al. (1999) devised a four-class typology based on five waves, and Jenkins et al. (2001) a five - class typology based on nine waves. All three typologies share one-off, recurrent, and persistent poverty in common. Table 7.2 presents a comparison of Jenkin et al.'s (2001) findings and Bourrea-Dubois and Maitre's (2004) application of Muffels et al.'s typology to the study of child poverty. Figures in parentheses represent the proportions of poverty prevalence, that is, the percentage of individuals who were poor at least once.

Table 7.2: A Comparison of longitudinal poverty classifications

Jenkins, Rigg, Devicienti 2001: 1991-1999	All (%)	Children (%)
Never poor: never poor during the accounting period.	53	45
Poor once: poor only once during the accounting period.	13 (28)	13 (24)
Recurrent poverty: either poor in any two consecutive waves separated by at least one spell of non-poverty; or three to six spells separated by at least two spells of non-poverty.	6 (13)	7 (13)
Short-term persistent: either poor in any two consecutive waves separated by at least one spell of non-poverty; or three to six spells separated by at least two spells of non-poverty.	19 (41)	25 (45)
Long-term persistent: at least seven to nine waves in poverty.	8 (17)	10 (18)
Prevalence (% ever poor)	46 (100)	55 (100)

Bourrea-Dubois and Maitre (2004): 1994-2001	All (%)	Children (%)
Persistent non-poor: never poor during the accounting period.	61	50
Transient poor: poor only once during the accounting period.	10 (26)	9 (18)
Recurrent poor: poor more than once, but never longer than 2 consecutive years	12 (32)	15 (30)
Persistent poor: poor for a consecutive period of at least three years.	16 (42)	27 (54)
Prevalence (% ever poor)	38 (100)	50 (100)

Sources: Jenkins et al. (2001) - Based on 9 waves of BHPS (1991-1999). Figures derived from Table 2.1, p.p. 22.
Bourrea-Dubois and Maitre (2004) - Based on 8 waves of BHPS (1994-2001). Figures derived from Table 3, p.p. 6.
Cross-sectional figures derived from Table 4.4.
Both tables are based on the 60 per cent of median income threshold.

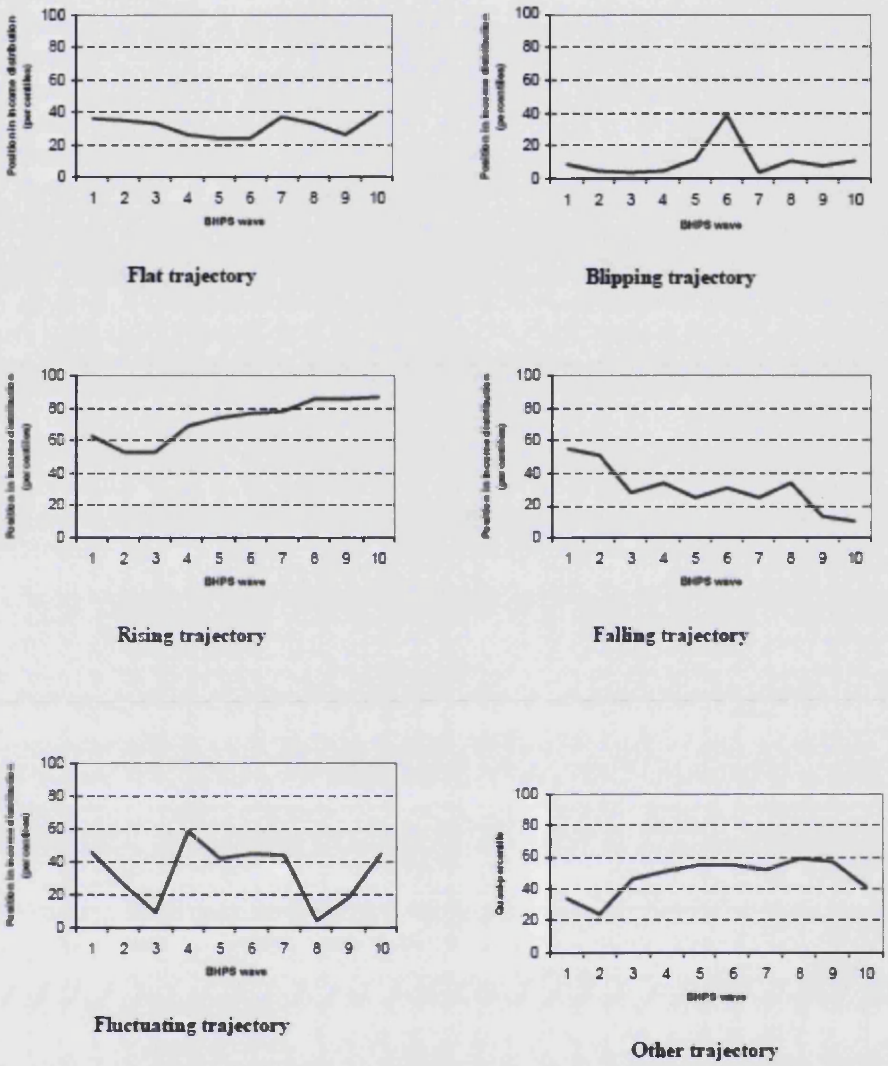
Both studies show that a large proportion of people experienced poverty at least once. At least half of all children were touched by poverty at some point in their lives. For the majority of people who ever experienced poverty, it was often short-lived through single or multiple episodes of poverty. Of those who were ever poor over a nine year period, approximately 30 per cent of all individuals and a quarter of children fell below the poverty line in only one year. Over half of the ever-poor experienced recurrent or short-term persistent poverty. Recurrent poverty arises because income mobility tends to be over a short distance: incomes do not increase sufficiently enough to lift individuals above the poverty line for a long enough period for them to build up their economic resources. Therefore, they tend to oscillate above and below the poverty line.

Jenkins et al.'s study shows that between 1991 and 1999, approximately one-tenth of individuals lived on low income continuously for between seven and nine years. Whilst this is a relatively uncommon experience overall compared to other trajectory types, this figure rises to a fifth as a proportion of those who are ever-poor. Moreover, short-term persistent/persistent poverty accounts for a greater proportion of prevalence than one-off or recurrent poverty. The rank of each typology category is the same for children and all individuals, however, children are less likely to be never poor than all individuals and more likely to be persistently poor.

A further development in the literature on poverty trajectories has been the use of income as a continuous variable. Using ten waves of the BHPS, Rigg and Sefton (2004) identified six income trajectories: flat, flat with blips, rising, falling, fluctuating, other (see Figure 7.1) and further distinguished between trajectories that led people into poverty and those which did not. This analysis extended the study by Gardiner and Hills (1999), which used four waves of the BHPS. Individuals were classified into one of six trajectories with the classification requiring individuals to cross a certain number of percentile boundaries. The rules were validated and refined by showing a group of people visual representations of actual income patterns over time and asking each person to classify these into each of the six income patterns.

Overall, around half of all individuals followed a broadly flat income trajectory, which was split approximately equally between those with a 'flat' and those with a 'flat with blip' trajectory. A quarter of individuals either had rising or falling trajectories and one eighth had fluctuating trajectories. A limitation of the categorisation rule is that around an eighth of the sample did not have an income trajectory that had a distinct classification (that is, they belonged to 'other'). Furthermore, whilst an iterative procedure of refining the categorisation was employed, the percentile cut-offs were arbitrary.

Figure 7.1: Types of income trajectories



Source: Rigg and Sefton (2004) p.p. 8

The varying lengths of time spent in poverty have different implications for the effects on standards of living. In a study examining the relationship between income and material deprivation over time using seven waves of the BHPS, it was found that the experience of a short spell of poverty was only weakly associated with deprivation (Berthoud et al., 2004). In contrast, those in long-run poverty suffered high levels of deprivation and a temporary escape from poverty did little to alleviate this. Short-term transitions into and out of poverty may be less detrimental than sustained periods of poverty as the former can be smoothed by the benefits system. Chapter 5 demonstrated that the magnitude of poverty churning raises questions about the extent to which movements above the poverty line represent a true escape from poverty. A one-off 'blip' may be the result of measurement error rather than a genuine spell of poverty.

With regards to longer episodes of poverty, the presence of true state and duration dependency in poverty means that the longer a person occupies a state of poverty, the lower his or her chances of leaving it. For those who do experience long-term poverty, the consequences may be much more debilitating than for those who experience shorter and temporary spells of poverty as savings are depleted, material deprivation increases, and debts may accrue and become unsustainable. Longitudinal studies have been unable to shed much light about the *actual* experiences of long-term poverty, however, qualitative research has explored this area. According to Kempson:

> *"People's experiences change the longer they live on a low income – from acute worry initially, through a period when they feel they are coping with the situation, and finally to chronic despair when they can see no light at the end of the tunnel."* (Kempson, 1996, p.p. 47)

Thus, the findings from the dynamic studies of poverty are not wholly positive. Whilst most of the people who experience a spell of poverty escape it after a short period, this must be balanced against the reality that for others the experience of long periods of poverty can be especially debilitating.

Critique of existing literature

Although the subjective categorization approach has yielded important insights into the nature of longitudinal poverty patterns, there are important methodological limitations. Firstly, it precludes the testing of whether the groups actually represent true variation in the population given that they are assumed ex ante. A related problem is the risk of simultaneously "over-fitting" and "under-fitting" the data, i.e., creating trajectory groups that reflect only random variation while at same time failing to identify groups with actual distinct trajectories (Nagin, 2005). Furthermore, subjective rules do not provide a basis for calibrating whether one particular cut-off rule is better than another for assigning group membership as acknowledged by Jenkins et al. (2001): *"Our definitions of persistent poverty for Indicator 2 could be challenged. We offer them not as definitive categorisations; rather they illustrate the potential difficulties of deriving a clear cut measure, while at the same time providing some potentially useful information*". (Jenkins et al., 2001, p.p. 20). As illustrated, the different cut-offs or number of categories in each typology makes it difficult to directly compare findings across studies with panel surveys of varying lengths. Cut-off definitions may have to be revised or new categories devised as the observation period increases with the availability of new panel waves.

For these reasons, more systematic methods are required for classifying the experiences of poverty according to their distinct trajectories in a more formal way. Dynamic conceptualisations of poverty such as the number or length of poverty spells fail to capture important aspects of poverty dynamics, for example, whether the risk of poverty within each group is increasing, decreasing, or remains stable over time. Furthermore, the classifications assume that each spell of poverty is independent of past spells.

This chapter takes account of these issues by using latent variable modeling techniques to examine poverty trajectories. It does this by determining: (i) the optimal number of distinct underlying latent poverty classes; and (ii) how individual characteristics predict membership in each of the clusters.

7.3 Modeling long-term trajectories of poverty

In this section, conventional latent growth modeling is first reviewed in order to introduce the necessary background for latent class growth analysis, which follows.

7.3.1 Conventional latent growth modeling

Latent growth modeling (LGM) estimates a latent growth trajectory using observed repeated measures as indictors of the underlying process (Curran and Bollen, 2001). Individual change can be represented through a two-level hierarchical model, the first level a within-person model (Level 1) and the second a between-person model (Level 2). The within-person model refers to how change fluctuates over time intra-individually, whereas the between-person model refers to the amount of variation across individuals. The within-person regression model yields a separate slope and intercept for each individual. In the between-person model , the within-person slopes and intercepts are treated as dependent variables which are regressed on individual-level independent variables (Raudenbush and Bryk, 2002).

The underlying assumption of this framework is that all individuals are drawn from a single population with common parameters (slopes, intercepts, and error variances) and that a single growth trajectory can approximate the whole population.

For binary variables, the growth parameters are estimated with a binary logistic regression model (Curran and Bollen 2001; Raudenbush and Bryk, 2002; Muthen, 2004). Thus, the probability of poverty is expressed as:

$$P(y_{it}=1)=\frac{1}{1+e^{-\operatorname{logit}(y_{it})}} \tag{1}$$

Level 1 (within person): $$logit(y_{it}) = \eta_{Ii} + \eta_{Si}\lambda_t + \eta_{Qi}\lambda_t^2 + \varepsilon_{it} \qquad (2)$$

y_{it} is individual i's score on poverty status, y, at time point t (t=1,2,...,12 years).

λ_t is the value of time at t.

η_{Ii} is the estimated intercept of the growth trajectory for i. It is the initial level of poverty for I at the start of the growth process.

η_{Si} is the estimated slope of the growth trajectory for i. It is interpreted as the change in the log-odds that individual i is in category j of the binary outcome for a one unit change in λ .

ε_{it} is the time specific error term for i at t

Because an individual's probability of poverty might increase or decrease in a non-linear fashion over time, a quadratic slope, η_{Qi}, is parameterised by λ_t^2. Higher order polynomials may also be included.

The subscripts i on the intercept and slope growth factors in equation (2) denote that these factors can vary across individuals over time (i.e., random effects). In order to estimate average effects for the whole sample, the intercepts and slopes of the Level 1 within-person model become the outcomes for the Level 2 between-person equations as follows:

Level 2 (between person):

$$\eta_{Ii} = \mu_I + \xi_{Ii} \qquad (3)$$

$$\eta_{Si} = \mu_S + \xi_{Si} \qquad (4)$$

$$\eta_{Qi} = \mu_Q + \xi_{Qi} \qquad (5)$$

$$logit(y_{it}) = (\mu_I + \lambda_t\mu_S + \lambda_t^2\mu_Q) + (\xi_{Ii} + \lambda_t\xi_{Si} + \lambda_t^2\xi_{Qi} + \varepsilon_{it}) \qquad (6)$$

μ_I in equation (3) represents the mean level of poverty across all individuals at the beginning of the growth process.

μ_S in equation (4) is the mean of the slope factor and denotes the rate of change of the poverty trajectory averaged across all respondents.

μ_Q in equation (5) is the mean of the curvi-linear growth factor.

Because the intercept factor represents initial probability of poverty at t=1, the factor loading on the slope factor, λ_t, is fixed at zero.

ξ_{Ii}, ξ_{Si} and ξ_{Qi} are normally distributed disturbance terms with zero means, variances $\sigma_I^2, \sigma_{S,}^2 \sigma_Q^2$, uncorrelated with ε_{it} and are independent across individuals. The variance of the intercept, σ_I^2, is the inter-individual variance in initial levels of poverty. The variance of the slope, σ_S^2, represents inter-individual variability in the rate of change in the probability of poverty over time. σ_Q^2 is the variance in the curvi-linear growth factor and shows variability in the rate at which the probability of poverty moves up or down over time.

Equations (3) - (5) can be substituted into equation (2) to form equation (6). The first parenthetical term represents the fixed effect of the model (i.e., the mean intercept and growth rate) and the second term represents the random effect (i.e., variance around the intercept and growth rate).

A major limitation of conventional LGM is the assumption of population homogeneity (i.e., all individuals share the same growth trajectory). One method of allowing for different sub-groups of individuals to follow heterogeneous growth trajectories is through multiple-group LGM in which different models are fitted based on observed grouping variables (for example, gender, employment status, etc.). However, this approach is unsatisfactory when the aim is identify unobserved subgroups. This limitation is addressed through latent class growth analysis.

7.3.2 Latent class growth analysis

Latent class growth analysis (LCGA) is known as a finite mixture model as it assumes that the population is comprised of heterogonous population classes with distinctive patterns of behavior. Heterogeneity is captured by k latent classes each with different growth parameters (Muthén, 2004).

As discussed above, the literature on poverty dynamics has suggested the existence of multiple patterns of poverty over time, thus, LCGA provides a more appropriate framework for poverty dynamics as the homogeneity assumption inherent in LGM could mask distinct trajectories. LCGA approximates the heterogeneity in possible poverty trajectories with a finite number of classes. These vary with respect to the probability of belonging to a particular poverty trajectory and the rate of change in the probability of poverty over time within each trajectory.

The LCGA framework introduces a categorical latent variable and uses repeated measures of the outcome variable to identify distinct latent classes of sub-populations who follow distinct growth trajectories. The categorical latent variable is expressed as c with k classes, c_i =(c_{i1}, $c_{i2},\ldots,c_{ik}$) where c_{ik} equals 1 if individual i belongs to class k and 0 otherwise. y_{it} is still expressed as a linear combination of the intercept, slope, and a time-related variable, however, the ηs no longer vary across individuals but across groups of individuals captured by the latent class variable.[35]

The growth intercept and slope factors can vary across classes, however, LCGA places some restrictions on the nature of the estimated latent classes. Growth parameter variances associated within each trajectory class are constrained to zero, thus, individuals within each class are constrained to the same slope and intercept. An implication of this is that all of the individual variation in development is accounted for by class membership, and any residual variation is seen as random error.

Similar to conventional LGM, a polynomial function can be used in LCGA to model the relationship between an outcome, in this case poverty status, and time (Nagin, 2005; Nagin and Tremblay, 1999; Kreuter and Muthén, 2007; Muthén, 2004).

The LCGA extension of (1) is:

$$P(y_{itk} = 1) = \frac{1}{1+e^{-\mathrm{logit}(y_{itk})}} \tag{7}$$

Level 1 ('within person'): $$logit\ (y_{itk}) = \eta_{Iki} + \eta_{Ski}\lambda_t + \eta_{Qki}\lambda_t^2 + \varepsilon_{itk} \tag{8}$$

[35] In recent years, such finite mixture models have increasingly been applied to diverse fields of enquiry seeking to identify groups with distinctive patterns of behavior. Examples include trajectories of social mobility (Sturgis & Sullivan, 2008), substance abuse (Muthén & Muthén, 2000, Xie *et al.,* 2006), and criminal careers and patterns of juvenile delinquency over time (Kreuter & Muthén, 2007, Nagin & Tremblay, 1999).

Level 2 ('between person'):

$$\eta_{Iki} = \mu_{Ik} \tag{9}$$

$$\eta_{Ski} = \mu_{Sk} \tag{10}$$

$$\eta_{Qki} = \mu_{Qk} \tag{11}$$

In equation (8), the subscript k denotes that the growth model parameters are free to vary across the classes, thus, y_{itk} represents poverty status for individual i within latent class k at time point t.

η_{Iki} is the intercept of trajectory k for individual i (i.e., initial level of poverty within each trajectory class).

η_{Ski} is the linear slope of trajectory k for individual i (the linear rate at which i's poverty level changes within each trajectory class over time).

η_{Qki} is the quadratic growth factor for i within each trajectory class.

ε_{itk} is the time specific residual for i within each trajectory class at time point t.

Individuals within each class are assumed to be homogeneous with respect to their developmental patterns, therefore, the variances of the intercept, slope and quadratic term are set to zero within each class in equations (9) – (11).

An alternative method to LCGA is growth mixture modeling (GMM) (Muthén and Shedden (1999). LCGA estimates a mean growth curve for each class, but assumes no individual variation around the mean growth curve. GMM, on the other hand, estimates both mean growth curves for each class and individual variation around these growth curves by estimating growth factor variances for each class. In other words, it adds a random effects component to Nagin's model. The implication of LCGA is that all individual growth trajectories within a class are undifferentiated. In contrast, GMM implies that each latent group is comprised of heterogeneous individual trajectories that can be described by a single probability distribution.

One advantage of GMM is that fewer groups are generally required to specify an adequate model, however, it is susceptible to heavy computational complexity as increasing the number of trajectory groups increases the number of variability parameters. Hipp and Bauer (2006) investigated whether GMM and LCGA models are vulnerable to multiple local optima of likelihood functions through a case study and Monte Carlo simulations. Their findings indicate that model complexity and the number of latent classes influences non-convergence or convergence on a local solution for both GMM and LCGA models, however, these problems are more serious for GMMs.

Furthermore, Nagin and Tremblay (2005) suggest that the addition of variability parameters leads to conceptual issues about what delineates one group from another. For LCGA, a group is a cluster of individuals who follow approximately a homogenous trajectory. In contrast, for GMM a latent group is a subpopulation of heterogeneous individuals that can be described by a single probability distribution.

As the aim of the study is to identify whether unique trajectories of poverty exist and, if so, whether each trajectory is associated with a distinctive profile of correlates (as opposed to identifying the determinants of within-class variation), LCGA is chosen over GMM as a more suitable method for the investigation.

7.3.2.1 Conditional models

Thus far, only unconditional models that do not control for the effects of covariates on trajectory groups membership have been considered. Conditional LCGA models introduce time-invariant predictors via multinomial logistic regression. This is useful as it allows for the effects of household and individual characteristics to be simultaneously controlled for and for statistically significant predictors that are common to all groups to be distinguished from those that are specific to particular groups.

The effect of x on membership of latent trajectory group, c, with K categories the multinomial logistic regression is specified as (Muthén, 2004):

$$P(c_i = k \mid x_i) = \frac{e^{\beta_{0k} + \beta_{1k} x_i}}{\sum_{c=1}^{K} e^{\beta_{0c} + \beta_{1c} x_i}} \tag{11}$$

Where $P(c_i = k \mid x_i)$ is the probability of membership in group k conditional on x.

β_{0k} is the intercept for class k.

β_{1k} is the regression of class k on covariate x.

As the K probabilities sum to 1, standardization is required by selecting a reference trajectory group, for example, K, and setting β_{0k}=0 and β_{1k}=0, which gives:

$$P(c_i = 1 \mid x_i) = \frac{1}{1+e^{-l}} \qquad (12)$$

where l is the log odds,

$$\log\left[\frac{P(c_i = k \mid x_i)}{P(c_i = K \mid x_i)}\right] = \beta_{0k} + \beta_{1k} x_i \qquad (13)$$

β_{1k} the change in the log odds of being in trajectory group k relative to the reference group K for a unit change in x. Initial period values are used for assessing the antecedents of trajectory group membership.

Muthen (2004) recommends a single-step procedure in which the covariates are included when estimating the LCGA model. This is because the conditional model can incorporate more information to identify the optimal number of classes. Nagin (2005) cautions against this approach. He argues that the introduction of predictors of group membership tends to have no impact on the nature of the trajectories themselves. This is because the trajectories are defined by a time-varying variable, whereas the predictors of trajectory group membership are time invariant. Therefore, they do not include information that will affect the actual shape of the trajectories. Their role is limited to differentiating group membership rather than defining the specific form of the trajectory over time. He further argues that if cross-tabulated profiles of group membership are being created based on the maximum posterior probability, unconditional models should be estimated because if conditional models are used, *"... the profiles will be contaminated with an element of circularity – the profiles will be partially a statistical product of the very same predictors that the profiles themselves are intended to identify."* (p.117). For these reasons, this study follows Nagin's approach.

7.3.3 Measures of Model Fit

In order to select the LCGA model that best fits the observed data, the optimal number of latent classes needs to be determined. Starting with a one-class model, an additional class added sequentially to ascertain the impact on model fit. There is no agreement on the best measure of model fit index to use or a benchmark value against which to select the final number of latent classes (McLachlan and Peel, 2000). Following the standards presented by Muthen (2004) and Nagin (2005), the optimal number of classes will be ascertained using a combination of i) formal statistical criteria, ii) predictive adequacy of the models, iii) classification quality, and iv) the shape of the trajectory classes.

i. Formal statistical criteria

a) Lo-Mendell-Rubin Likelihood Ration Test (LMR LRT)

The conventional likelihood ratio test for comparing a k-1 and a k-class model is not appropriate for finite mixture modeling. When comparing nested models, parameter values of the *k*-class model are set to zero to specify the *k-1*- class model. This results in the likelihood ratio statistic not being chi-square distributed due to the class probability parameter being at the border of its admissible space (Muthén, 2004). Lo, Mendell, and Rubin (2001) have suggested using an adjusted likelihood ratio test, the Lo-Mendell-Rubin (LMR LRT) test to evaluate the optimal number of classes (Muthén 2004). This applies a corrected likelihood ratio distribution for testing $k - 1$ classes against k classes. A significant chi-square value indicates that the $k - 1$ class model should to be rejected in favor of the k-class model.

b) Bayesian Information Criterion (BIC)

Schwarz (1978) recommends the Bayesian information criterion (BIC) for discriminating among competing models, particularly those that are non-nested. It aims to balance goodness-of-fit and parsimony and is based on the difference between G^2 (which is the likelihood ratio chi-square test) and a "penalty" term, which is a function of the number of parameters (P) in the model and sample size (N):

$$BIC = G^2 - P \log N \qquad (14)$$

The first term measures the improvement in model fit that is gained from additional parameters. The second term acts as a counterbalance to increasing model complexity by imposing a penalty for the addition of more parameters. The addition of extra parameters is only desirable if the resulting increase in fit is larger than the penalty for a more complex model. The model with the smaller BIC provides a better fit to the data.

ii. Predictive adequacy

Posterior probabilities and the entropy value are assessed to ascertain the accuracy of the model in assigning individuals to each trajectory group. Posterior probabilities of group membership measure the probability of an individual belonging to each of the model's k trajectory groups given his/her measured status at each of the t waves. They are known as 'posterior' probabilities as they are post-model estimations using the model's estimated coefficients and are calculated as (Nagin, 2005):

$$\hat{P}(k \mid Y_i) = \frac{\hat{P}(Y_i \mid k)\pi_k}{\sum_k^K \hat{P}(Y_i \mid k)\pi_k} \qquad (15)$$

where Y_i is a vector containing individual *i*'s poverty status at each wave *t*, y_{it}

The posterior probability $\hat{P}(k \mid Y_i)$ is the estimated probability of individual *i*'s membership in group *k* given observed membership in each of the *t* measurement periods.

π_k is the proportion of individuals in group k (i.e. the size of each trajectory group).[36]

Posterior probabilities provide an objective basis for classifying individuals to the trajectory group that most closely reflects their poverty history: they are assigned to the group for which their posterior probability is the largest. For a classification in a specific latent trajectory group to be reliable, individuals must have high posterior probabilities for belonging to a specific class and low posterior probabilities for belonging to the other groups.

iii. Classification quality

Average posterior probabilities can be used to indicate the precision of classification and, therefore, the extent to which the classes are distinct. A *KxK* table can be constructed with rows corresponding to the probability of the most likely trajectory group membership. The column entries denote the average posterior probability of membership over the trajectory groups (Nagin, 2005). Diagonal values approaching 1 and off-diagonal values approaching 0 indicate good classification quality, thus, individuals are well-classified in the most likely class and have low probabilities of being assigned to other groups. With regards to an acceptable level of classification, a minimum threshold suggested by Nagin (2005) is that the average posterior probability for assignment should be at least 0.7 for all groups.

Finally, the entropy value (*E*) is calculated, which is a standardised summary measure based on the posterior probabilities from each model (Ramaswamy et al., 1993; Muthén and Muthén, 2000). Entropy does not measure model fit but provides an indication as to how well a model classifies individual growth

[36] The probability of group membership, π_k, is distinct from the posterior probability of group membership. The former measures the aggregate size of each trajectory, whereas the latter measures the probability that an individual with a specific sequence of observed outcomes belongs to a specific trajectory group over the *t* measurement periods.

trajectories into the categorical latent classes and the degree of separation between (i.e., classification accuracy). E is calculated as:

$$E_K = 1 - \frac{\sum_i \sum_k (-\hat{p}_{ik} \log \hat{p}_{ik})}{n \log K} \qquad (16)$$

Where E_K is the entropy value for a K-class model, $\hat{p}_{ik}$ is the estimated conditional probability for individual i in class k, and n is the sample size. It ranges from 0 to 1 with higher values indicating better classification of individuals into the latent classes.

iv. Shape of the trajectory classes

A plot of the growth curves for each latent trajectory group can help to establish the extent to which the shapes and locations of class trajectories are distinct and represent unique patterns over time (Kreuter and Muthén, 2007). The addition of a new group to the model may result in the division of a trajectory group into two smaller qualitatively similar trajectories, which may suggests over-fitting of the model (Nagin and Tremblay, 2001). The final decision on the optimal model should also be guided by theoretical insights. If the similar classes are not substantively meaningful, a more parsimonious model may be preferable for summarising the distinctive features of the data.

7.3.4 Missing data

A feature of panel surveys is missing data, which arises through sample attrition over time. A common and simple approach for dealing with missing data is listwise deletion in which cases with incomplete information are omitted from the analysis sample. This not only results in a significant reduction in sample size, but also biased parameter estimates from selection effects if non-response is related to observed and or unobserved characteristics.

Two processes underlying non-response are that the data are Missing Completely at Random (MCAR) or Missing at Random (MAR) (Little and Rubin, 2002). MCAR assumes that the probability that an observation (Y_i) is missing is uncorrelated with the value of Y_i or any observed and unobserved predictors in the model. The unbalanced panel may not necessarily bias parameter estimates if there are no systematic difference between those who enter, leave, or stay in the panel. MAR assumes that pattens of missing data do not depend on the value of Y_i after controlling for other covariates. Thus data on low income would not be MCAR if, for example, if poor individuals are less likely to report family income than individuals with higher income, are more likely to be lone parents, live in temporary accommodation, or have lower levels of education.

All models presented in this chapter are estimated using MPlus 5.1 (Muthen and Muthen, 2007). A useful feature of this package is that is includes a number of options for handling missing data. A full maximum-likelihood estimator is used, which assumes that the data are MAR. This allows maximum use of data on cases with one or more years of missing data.

7.4 Hypotheses

Chapter 6 tested the temporalisation, democratisation and poverty persistence hypotheses for short-term transitions. This chapter aims to test the same hypotheses using the whole series of poverty observations over twelve years.

If the persistent poverty hypothesis holds true, it is expected that there are only two distinct trajectories of long-term poverty (i.e., k=2 in the LCGA model), that is, those who are permanently poor or never poor. On the hand, if the temporalisation thesis holds true, it is expected that there are more than two distinct trajectories to reflect shorter/transient spells of poverty (i.e., k>2). In addition to the permanently poor or never poor groups, it is expected that additional trajectories exist to reflect the risk of poverty increasing and/or decreasing over time. These hypotheses will be explored through tests of model fit to determine the optimal number of classes and through the shapes of the trajectories.

The democratisation hypothesis predicts poverty extends more widely across society, thus, it is expected that individuals belonging to specific trajectory groups are heterogeneous with respect to their characteristics – the long- or short-term poor are not defined by traditional marginalised groups. Furthermore, those with protective characteristics are not shielded from the experience of poverty. This hypothesis will be explored through an examination of the determinants of trajectory group membership using cross-tabulations, multinomial logistic regression, and simulated probability profiles.

7.5 Empirical results

The analysis is undertaken in four steps. Firstly, unconditional LCGA models are estimated in order to determine the optimal number of trajectory groups and the shapes of the trajectories. The determinants of trajectory group membership are explored through cross-tabulations of covariates by trajectory class and a multinomial logistic regression analysis in order to ascertain whether the antecedents of trajectory group membership lead to qualitatively different pathways of poverty dynamics. Finally, simulated predicted probabilities of trajectory group membership based on specific values of the antecedents. [37]

7.5.1 Determining the optimal number of trajectory groups

To identify the optimal number of distinct poverty trajectories, LCGA models with one to eight classes were estimated for the general population and children. This section evaluates the best fitting model using the selection criteria presented in Section 7.3.3. The model fit statistics for children are presented in Table 7.3. The estimates for the general population are presented in Table A7.1 in the Appendix.

The BIC values continue to decrease as the number of classes increases, however, the rate of increase is relatively small after the addition of four classes. As there is no dip at which point the values start to increase, the BIC index is not able to clearly identify the preferred number of classes. According to the LMR LRT, the five-class model has a lower significance, indicating that the four-class model has a better fit. The LMR LRT comparing models with three and four trajectory groups indicates that the addition of a fourth class significantly improves model fit. The entropy values suggest that individuals are more accurately classified in the four-class model (E=0.622) than in the five-class model (E=0.613).

Table 7.4 reports the average posterior probability of membership for children in each of the four groups for those individuals that were assigned to them. The corresponding table for the population is Table 7.2A in the Appendix. The average posterior assignment probabilities along the main diagonal for the four class-class model all exceeded Nagin's minimum acceptable level of classification (0.7) and range from 0.704 to 0.839. This suggests that individuals were well classified in the most likely class and did not have high probabilities of being placed in another class. Thus, for example, cell (3,3) shows that of those individuals for whom the most likely membership was in latent trajectory group 3, the average posterior probability was 0.839.

The five-class model has a less precise posterior probability classification table (Table 7.5) compared to the four-class model, with three trajectory groups (1, 2 and 4) having an average probability below 0.7. A comparison of the posterior probabilities for the four and five class model show that groups 1, 2 are of a similar size, whereas groups 3 and 4 becomes much smaller with the addition of another class. These results suggest that the additional trajectory group in the five-class model has 'splintered' from one or

[37] The descriptive, multinomial logistic regression, and predicted probability analysis are undertaken in Stata 9.1.

more larger groups in the four-class model rather than being a distinct class with a unique trajectory pattern. [38]

For reasons of parsimony and based on the statistical evidence, the four-class model is chosen as the optimal model for representing the trajectory patterns of poverty over time. This result holds for the general population also. [39]

Table 7.3: LCGA model fit statistics: children (60 % of median income poverty line)

Classes	LL	N parameters	BIC	Entropy	LMR LRT	LMR LRT p-value k-1
1	-16197.73	3	32421.13			
2	-12757.33	7	25574.56	0.738	6685.51	0.000
3	-12427.51	11	24949.16	0.623	640.92	0.000
4	-12262.51	15	24653.38	0.622	320.64	0.000
5	-12210.65	19	24583.9	0.613	100.77	0.0192
6	-12184.76	23	24566.36	0.618	50.3	0.1977
7	-12163.76	27	24558.59	0.544	21.31	0.1736
8	-12134.73	31	24534.76	0.634	58.03	0.1751

Source: Derived from the BHPS 1991-2002 unbalanced panel.

Table 7.4: Classification table: children, 4-class model

		Average posterior probability			
		Class 1	**Class 2**	**Class 3**	**Class 4**
Most likely group	**Class 1**	**0.710**	0.093	0.102	0.095
	Class 2	0.112	**0.704**	0.082	0.102
	Class 3	0.091	0.058	**0.839**	0.012
	Class 4	0.165	0.089	0.027	**0.719**

Source: Derived from the BHPS 1991-2002 unbalanced panel.

[38] These results using FIML estimation are similar listwise deletion of cases (i.e. using a balanced panel), therefore the results are robust to different missing data specifications.

[39] The optimal number of classes (i.e., 4) is robust to the inclusion of covariates in a joint-estimation check of robustness.

Table 7.5: Classification table: children, 5-class model

Most likely group		Average posterior probability				
		Class 1	**Class 2**	**Class 3**	**Class 4**	**Class 5**
	Class 1	**0.699**	0.072	0.112	0.052	0.065
	Class 2	0.067	**0.676**	0.085	0.08	0.093
	Class 3	0.084	0.146	**0.71**	0.03	0.03
	Class 4	0.106	0.152	0.071	**0.617**	0.053
	Class 5	0.052	0.07	0.014	0.035	**0.829**

Source: Derived from the BHPS 1991-2002 unbalanced panel.

7.5.2 Description of the poverty trajectories

Table 7.6 presents the model parameters for the four trajectory groups for children and highlights distinct patterns of poverty dynamics over time. The corresponding table for the population is Table A7.4 in the Appendix. The shapes of the different trajectories derived from the 4-class model can be seen more clearly in Figure 7.2. This plots the model-predicted probability of poverty at each time point for each poverty trajectory.

The largest group is labeled as the non-poor trajectory (NP). Children were more likely to belong to the NP group than any other group, however, they had a lower likelihood than all individuals of doing so (56 per cent versus 62 per cent). Within this group, both samples had a similarly minimal exposure to the risk of poverty, which changed very little between 1991 and 2002: in any given year, individuals in the NP group had, on average, a 2 per cent chance of being poor.

In stark contrast, the permanent poor group (PP), which constitutes a much smaller proportion of children (14 per cent), exhibited sustained and high levels of exposure to poverty. Children had a higher risk of belonging to this trajectory group than all individuals (14 versus 11 per cent). Over time, both groups had a similar probability of poverty, which increased from 0.71-0.75 in 1991 to 0.85 by 1991 before declining to 0.69-0.72 by 2002. This pattern of change over time is evident in the cross-sectional data (Chapter 4) and in the Markov analysis of persistent poverty between two consecutive years (Chapter 5).

The remaining two groups represent trajectories of transient poverty, i.e., the moving out of poverty (OP) and the moving into poverty (IP) groups. Children were more likely than all individuals to belong to the OP group (18 per cent versus 14 per cent) and slightly less likely to belong to the IP group (11 per cent versus 13 per cent). The OP group experiences an improvement in income over time. Individuals began with a moderately high probability of poverty (0.56), however, this declined steadily to the same level as the most advantaged group by 2002 (0.04). Although children were more likely than all individuals to belong to this group, they had a slightly higher risk of being poor in most years.

Individuals in the IP group followed the opposite path. They experienced an increased likelihood of economic disadvantage over times. Their initial risk of poverty was only slightly higher than the persistently non-poor group, but they were increasingly likely to live in poverty over time. By 2002, children in particular were as likely as the persistent poor of living in poverty. One notable feature of the chart is that after 1997, the children's risk of poverty increased at a faster rate than that of all individuals. These findings confirm the "flat", "rising" and "falling" income trajectories found by Rigg and Sefton (2004).

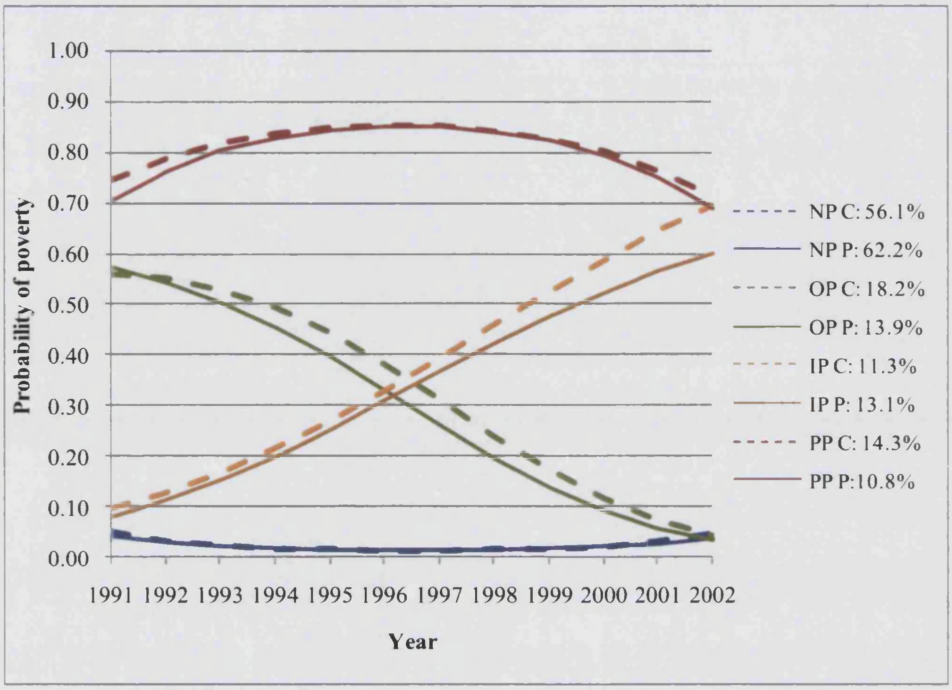
These findings lend support for the temporalisation hypothesis: even from a longer-term perspective, poverty appears to be a widely shared experience in the population. A relatively large proportion of individuals experience a temporary stretch of poverty by either over-coming or entering it. Furthermore, relatively few individuals experience a permanent episode of poverty.

Table 7.6: Estimated parameters for the four-class model: children

Trajectory k	**Intercept** η_{Ik}	**Linear Slope** η_{Sk}	**Quadratic Slope** η_{Qk}
OP	-0.840 (0.255)***	-0.010 (0.084)	-0.027 (0.008)***
IP	-3.306 (0.489)***	0.320 (0.172)*	-0.004 (0.014)
NP	-3.983 (0.215)***	- 0.450 (0.078)***	-0.040 (0.007)***
PP	0.000 - (N.A.)	0.266 (0.069)***	-0.025 (0.007)***

Source: Derived from the BHPS 1991-2002 unbalanced panel.
Coefficients are in logit scale; * p<0.10 **p<0.05 ***p<0.01
OP=Moving out of poverty; IP=Moving into poverty; NP=never poor; PP=permanently poor

Figure 7.2: 4-class estimated probabilities for children and the population

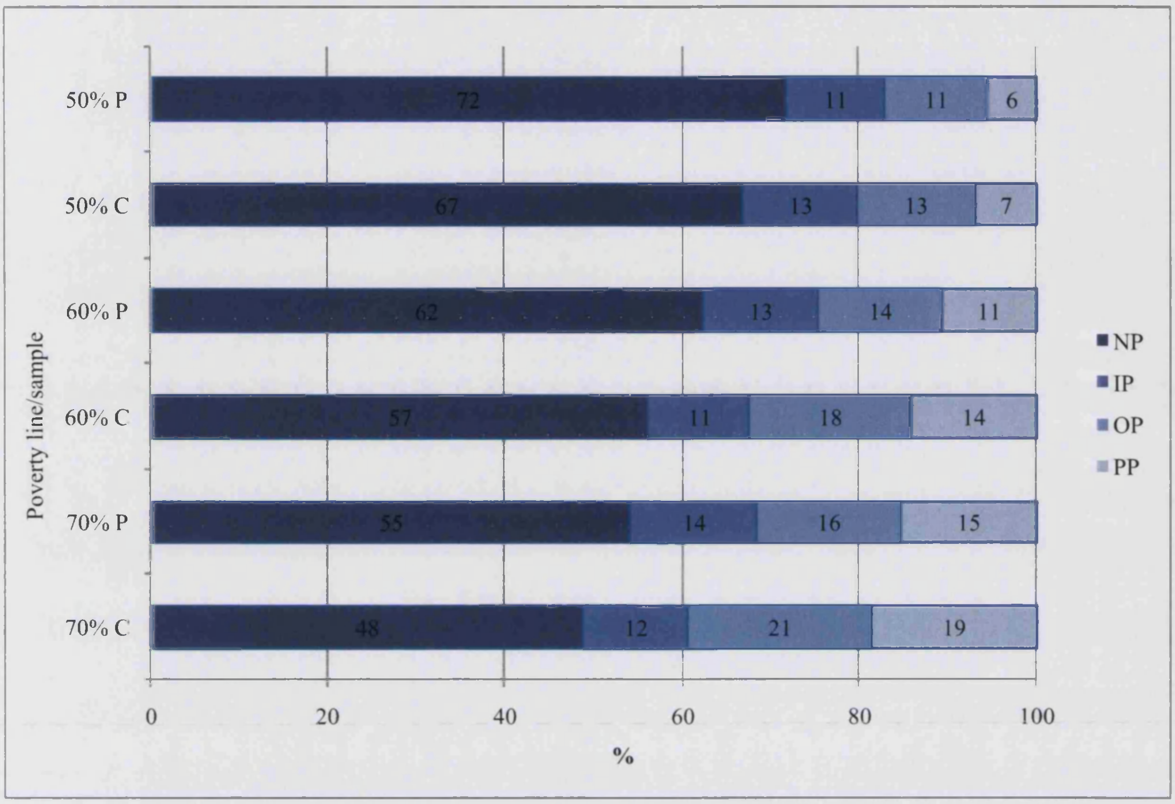


Source: Derived from the BHPS 1991-2002 unbalanced panel.

A sensitivity analysis was undertaken to assess the robustness of the findings. Figure 7.3 compares the probability of trajectory group membership by poverty line for children (C) relative to the general population (P). A number of distinct patterns are evident. As expected, raising the income threshold increases the number of people who are identified as belonging to a poverty trajectory. At each threshold, the proportion of ever poor children exceeds that of all individuals by 11-14 per cent. For example, at the 60 per cent threshold, 44 per cent of children are ever poor compared with 38 per cent of all individuals.

With regards to the specific trajectories, at the 50 per cent threshold, children are as likely as the population to be in the PP group but are more likely at the 60 and 70 per cent thresholds. Children have a greater tendency of belonging to the OP group than the population at all income thresholds. Children are almost as likely as the population to belong to the IP group. The size of this group remains stable across thresholds (11-13 per cent) for both samples. The OP and PP groups are 1.5 and 3 times as large, respectively, at the 70 per cent level compared with the 50 per cent level for both groups.

Figure 7.3: Sensitivity of the size of trajectory group membership to various poverty lines



Source: Derived from the BHPS 1991-2002 unbalanced panel; C=children; OP=Moving out of poverty; IP=Moving into poverty; NP=never poor; PP=permanently poor; P=population, C=children.

7.5.3 Determinants of poverty trajectories

7.5.3.1 Descriptive analysis

This section explores whether the four trajectories are differentially associated with various social and economic correlates. This allows one to establish whether each of the poverty trajectories is distinctive in terms of the groups of people affected. The analysis is also useful for ascertaining whether there any variables have general or specific effects across trajectory classes. The profiles are based on most likely latent class probabilities. Table 7.7 presents the findings for children, and Table A7.5 in the Appendix presents the findings for the population. The shaded cells 'map' which sub-groups of individuals are over-represented within each of the trajectories compared with overall trajectory group size.

A number of interesting features emerge from the data. The type of poverty experienced varies markedly between subgroups. As expected, belonging to heads who are male, with A-Level or higher qualifications, or household where all adults or at least adult (but not all) are in paid work is associated with the highest likelihood of being never-poor. However, not all sub-groups with positive attributes are protected from poverty. Whilst three-quarters of children in households where all adults or at least one adult are in paid work belong to the never poor group, one in twelve children experience permanent poverty and one in six children experience transient poverty (moving in or out of poverty). A similar pattern holds for individuals belonging to heads with A-Level or higher qualifications.

Certain disadvantaged groups were more likely to move out of poverty over time than into poverty: for both samples, approximately one-fifth of individuals belonging to heads with no qualifications or to households with no paid workers experienced improved economic conditions. 20 per cent of children belonging to lone parents experienced moved out of poverty over the twelve waves, compared to 13 per cent of all children.

Certain factors had a greater impact on children's likelihood of belonging to particular trajectory groups. Children belonging to workless households are approximately twice as likely to experience permanent poverty (47 per cent) than the general population (26 per cent). The most important risk factor associated with children moving into poverty is belong to head who is under the age of 25 (13 per cent). For the population, however, the presence of four or more children is the largest risk factor (15 per cent).

Family size has different associations across trajectory classes. Whilst the presence of additional children is associated with a lower risk of children moving into poverty compared with all individuals, it has a large effect on the risk of permanent poverty: 49 per cent of children with three or more siblings are classified as permanently poor compared with 35 per cent of all individuals with four or more children in the household. For up to 3 children (2 siblings) in the household, children face similar chances of moving out of poverty as the population (Table A7.5). However, for 4+ children (3+ siblings), children are much less likely than the population to move out of poverty (13 per cent versus 21 per cent).

It is interesting to note how these findings compare with existing studies. Whilst Rigg and Sefton (2004) utilised income as the variable for constructing trajectory profiles, there are a number of similar findings in terms of the kinds of individuals who are more likely than average to be following particular trajectories. For example, children, lone parents, adults in couples with older children, those initially unemployed, and those with low incomes are more likely to have experienced rising incomes over the ten year period. Adults in childless couples are most likely to have falling incomes over time. Rigg and Sefton also examined the relationship between income trajectories and poverty (poverty line used was the bottom quintile of equivalised household income, which corresponded closely with 60 per cent of median equivalised household income). They found that individuals who were children or lone parents in wave one were not only more likely to experience rising incomes but were also more likely to be moving out of poverty than other groups who were on a rising trajectory.

Table 7.7: Profile of trajectory group membership: children

	PP	OP	IP	NP	Group size
All individuals	**16.07**	**12.61**	**7.20**	**64.12**	**100**
Sex of head					
Male	12.16	11.59	6.43	69.81	42.04
Female	19.08	13.40	7.79	59.73	57.96
Tenure					
Owned	**7.93**	**8.56**	5.84	77.66	68.52
Social rented	**36.76**	**22.17**	9.12	**31.95**	26.10
Private rented	15.45	14.92	**12.57**	57.07	5.38
Education level of head					
A-Levels or above	**7.81**	**8.42**	5.98	77.79	35.21
O/CSE Level	16.33	14.77	8.31	60.59	41.89
No qualifications	**32.65**	**16.96**	7.50	**42.88**	22.90
Family type					
Couple with children	11.68	11.08	7.26	69.98	81.72
Single with children	**38.02**	**20.28**	6.91	**34.79**	18.28
Age of head					
<=25	**27.29**	**19.06**	**13.18**	**40.47**	4.19
26-34	17.04	15.22	8.47	59.27	35.23
35-44	12.19	10.46	**4.80**	72.55	45.10
45+	17.15	**6.69**	6.40	69.77	15.49
Household emplyment status					
All adults in work	**7.89**	10.03	6.34	75.74	61.62
At least one adult in paid work but not all	**8.13**	10.27	7.61	73.98	18.58
Household without paid work	**46.53**	**22.03**	8.87	**22.58**	19.80
Number of siblings					
0	**9.65**	9.35	6.37	74.63	26.98
1	12.76	12.33	6.64	68.26	42.85
2	20.18	**18.49**	8.45	52.88	21.57
3+	**48.80**	12.98	**10.34**	**27.88**	8.59
Disability status of head					
Non-disabled	15.84	12.58	7.21	64.37	98.94
Disabled	**28.89**	14.44	6.67	50.00	1.06
N. Long-term sick in household					
0	15.88	12.43	7.25	64.44	96.23
1	18.58	15.85	6.56	59.02	3.41
>4	**38.10**	**28.57**	**0.00**	**33.33**	0.36

Source: Derived from the BHPS 1991-2002 unbalanced panel.
Notes: Characteristics at t=1.
Lightly shaded boxes indicate substantially lower-than-average probabilities (at least 30 per cent lower than average). Darkly shaded boxes indicate substantially higher-than-average probabilities (at least 30 per cent higher than average).
OP=Moving out of poverty; IP=Moving into poverty; NP=never poor; PP=permanently poor
N=2849

7.5.3.2 Multinomial logistic regression analysis

Whilst the descriptive profiles of trajectory group membership provide insights into how group membership varies with individual or household characteristics, a multiple regression model is required for simultaneously controlling for the effects of several predictors and for distinguishing between statistically significant predictors that are common to all groups and those that are specific to particular groups. This is undertaken using multinomial logistic regression, which provides the odds of a child being assigned to one trajectory class versus another conditional on antecedents measured at t=1.

Tables 7.8 and 7.9 present the results for children and the general population, respectively. The conditional model contains $2^4=16$ sets of contrasts, however, not all are of substantive interest. The non-poor group serves as the reference class for the models in columns one to three. The model in column four contrasts the factors that increase the likelihood of moving into poverty relative to moving out of poverty.

Table 7.8: Determinants of trajectory group membership (odds ratios): children

Multinomial logistic regression contrast	IP v NP	PP v NP	OP v NP	IP v OP
Sex of the head (ref=male)				
Female	1.175	0.925	0.892	1.317*
	(0.141)	(0.106)	(0.092)	(0.196)
Accommodation (ref=owned)				
Social rented	1.986***	3.186***	2.956***	0.672**
	(0.292)	(0.373)	(0.336)	(0.116)
Private rented	2.075***	1.438*	1.681***	1.234
	(0.396)	(0.271)	(0.296)	(0.282)
Highest qualification of head (ref='A'-Levels or higher)				
O/CSE Level	1.458***	1.919***	1.743***	0.837
	(0.193)	(0.234)	(0.197)	(0.130)
No qualifications	1.441**	2.726***	1.983***	0.727*
	(0.242)	(0.366)	(0.273)	(0.148)
Parental type (ref=couple)				
Single with children	1.150	2.450***	2.031***	0.566***
	(0.211)	(0.313)	(0.276)	(0.114)
Age of head (ref= <=25)				
Age 26-34	0.615**	0.778	1.001	0.614**
	(0.123)	(0.136)	(0.178)	(0.134)
Age 35-44	0.304***	0.576***	0.654**	0.465***
	(0.065)	(0.110)	(0.121)	(0.113)
Age 45+	0.463***	0.846	0.411***	1.125
	(0.111)	(0.175)	(0.096)	(0.334)
N. workers in household (ref=all adults in paid work)				
At least 1 paid worker but not all	1.071	1.138	1.049	1.021
	(0.152)	(0.154)	(0.121)	(0.170)
No paid workers	2.638***	7.897***	3.513***	0.751
	(0.430)	(0.981)	(0.463)	(0.135)
N. siblings (ref= only child)				
1 sibling	1.298*	1.667***	1.482***	0.875
	(0.187)	(0.211)	(0.172)	(0.153)
2 siblings	2.169***	3.146***	2.593***	0.837
	(0.366)	(0.455)	(0.356)	(0.161)
3+ siblings	4.589***	11.338***	2.881***	1.593*
	(0.412)	(0.236)	(0.580)	(0.411)
Disability status of head (ref=not disabled)				
Disabled	0.933	1.092	0.900	1.037
	(0.422)	(0.341)	(0.320)	(0.532)
Long term sick (N)	0.905	1.005	1.083	0.836
	(0.148)	(0.117)	(0.119)	(0.142)
Constant	0.080***	0.032***	0.060***	1.318
	(0.020)	(0.012)	(0.011)	(0.352)
N	2849	2849	2849	2849
Model chi2	2043.01	2043.01	2043.01	2043.01
P-value	0.000	0.000	0.000	0.000

Source: Derived from the BHPS 1991-2002 unbalanced panel.
Notes: Standard errors in parentheses
Characteristics at t=1; * $p<0.10$ ** $p<0.05$ *** $p<0.01$
Poverty line=60 per cent of median income
OP=Moving out of poverty; IP=Moving into poverty; NP=never poor; PP=permanently poor

Table 7.9: Determinants of trajectory group membership (odds ratios): population

Multinomial logistic regression contrast	IP v NP	PP v NP	OP v NP	IP v OP
Sex of the head (ref=male)				
Female	1.047	0.975	0.925	1.132*
	(0.061)	(0.068)	(0.053)	(0.084)
Accommodation (ref=owned)				
Social rented	1.640***	1.982***	2.568***	0.639***
	(0.115)	(0.142)	(0.163)	(0.053)
Private rented	1.283***	1.547***	1.863***	0.689***
	(0.122)	(0.151)	(0.173)	(0.087)
Highest qualification of head (ref='A'-Levels or higher)				
O/CSE Level	1.539***	1.924***	1.790***	0.860*
	(0.130)	(0.153)	(0.128)	(0.076)
No qualifications	1.894***	3.127***	2.396***	0.790**
	(0.142)	(0.264)	(0.177)	(0.075)
Family type (ref=single with no children)				
Pensioner single	1.689***	2.107***	1.565***	1.079
	(0.238)	(0.277)	(0.252)	(0.187)
Pensioner couple	1.345**	1.289*	0.924	1.456**
	(0.183)	(0.173)	(0.124)	(0.255)
Couple with children	1.935***	1.521**	1.143	1.693**
	(0.334)	(0.300)	(0.179)	(0.362)
Couple with no children	1.491***	0.85	0.941	1.585***
	(0.155)	(0.112)	(0.103)	(0.223)
Single with children	2.498***	4.250***	2.260***	1.105
	(0.497)	(0.892)	(0.387)	(0.252)
Age of head (ref= <=25)				
Age 26-34	0.721***	0.615***	0.915	0.788*
	(0.073)	(0.064)	(0.096)	(0.100)
Age 35-44	0.598***	0.383***	0.729***	0.819
	(0.072)	(0.056)	(0.082)	(0.112)
Age 45+	1.103	0.632***	1.067	1.034
	(0.113)	(0.078)	(0.113)	(0.144)
N. workers in household (ref=all adults in paid work)				
At least 1 paid worker but not all	1.240***	1.392***	1.039	1.193*
	(0.096)	(0.149)	(0.087)	(0.123)
No paid workers	2.205***	8.783***	3.901***	0.565***
	(0.169)	(0.701)	(0.273)	(0.052)
N. children (ref= 1 child)				
0 children	1.350*	0.904	1.598***	0.845
	(0.236)	(0.182)	(0.254)	(0.187)
2 children	1.221	1.867***	2.532***	0.482***
	(0.224)	(0.394)	(0.414)	(0.114)
3 children	2.033***	3.021***	3.963***	0.513***
	(0.397)	(0.653)	(0.683)	(0.122)
4+ children	4.587***	12.237***	7.384***	0.621*
	(1.011)	(2.995)	(1.502)	(0.164)
Disability status of head (ref=not disabled)				
Disabled	1.014	0.573***	0.859	1.181
	(0.142)	(0.094)	(0.120)	(0.202)
Long term sick (N)	0.953	1.184***	0.898***	1.062
	(0.044)	(0.032)	(0.042)	(0.061)
Constant	0.042***	0.019***	0.029***	1.462**
	(0.016)	(0.000)	(0.000)	(0.250)
N	11616	11616	11616	11616
Model chi2	5325.35	5325.353	5325.353	5325.35
P-value	0.000	0.000	0.000	0.000

Source: Source: Derived from the BHPS 1991-2002 unbalanced panel.
Notes: Standard errors in parentheses; Poverty line=60 per cent of median income.
Characteristics at *t*=1; * p<0.10 **p<0.05 ***p<0.01
OP=Moving out of poverty; IP=Moving into poverty; NP=never poor; PP=permanently poor

It is found that significant factors that are associated with the risk of poverty across all three trajectory groups for both samples are:

- tenure
- education level
- age of the head being between 35-44
- households with no paid workers
- the presence of three or more children

Sex of the head has no significant effect on the probability of poverty for either children or the general population when the non-poverty group is used as the base comparator. This lack of association is surprising, however, it is possible that work status and family composition (in particular, lone parenthood) mediated this effect.

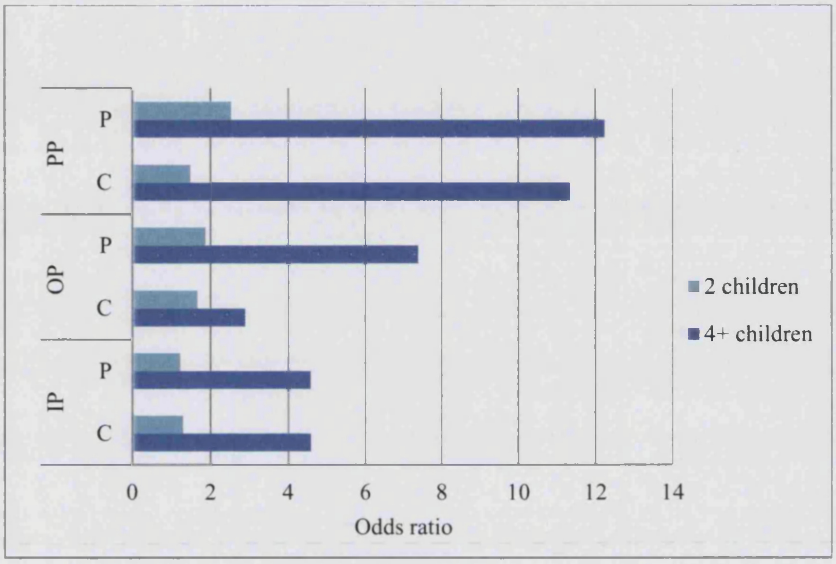
In terms of the main differences between samples, having at least one employed person in the household but not all, the number of long-term sick and disability status of the head has no significant effect on trajectory group membership for children. However, for the general population, having at least one employed person relative to all persons being employed increases the risk of moving into and permanent poverty. Furthermore, an increase in the number of long-term sick people in the household increased the likelihood of permanent poverty and reduced the likelihood of moving out of poverty. Belonging to a household with a disabled head is only associated with permanent poverty. An explanation as to why long-term illness or disability does not appear to have a stronger impact on poverty trajectory membership is that these groups of people are often disadvantaged to begin with (for example, lower economic activity rates and greater likelihood of having incomes close to the poverty line). Consequently, they are constrained in the degree of downward movement (Rigg and Sefton, 2004).

The magnitude of important covariates on trajectory group membership is now assessed. Odds ratios greater than one correspond to a positive association between trajectory group membership and the explanatory variable whilst odds ratios less than one correspond to a negative association.

As expected, an increase in the number of children in the household increases the likelihood of belonging to each of the poverty trajectories, with the effects being most pronounced for permanent poverty. The presence of four or more children/ three or more siblings in the household is the single largest risk factor for both samples. Figure 7.4 shows that children with one sibling are 1.7 times more likely to be permanently poor than never poor, whereas the odds ratio for children with three or more siblings is 11.

The effect of the number of children has a generalised effect on the likelihood of moving into poverty for both samples. However, the general population is approximately 2.5 times more likely than children to move out of poverty when there are 4 or more children in household (OR=2.9 versus 7.4).

Figure 7.4: Odds ratios for the impact of the number of children on trajectory group membership



Source: Derived from the BHPS 1991-2002 unbalanced panel.
Odds ratios derived from tables 7.8 and 7.9 (other variables held constant). The reference category for the dependent variable is never poor. The reference category for the explanatory variable is 1 child for the population model and 0 siblings for the children's models.
OP=Moving out of poverty; IP=Moving into poverty; NP=never poor; PP=permanently poor

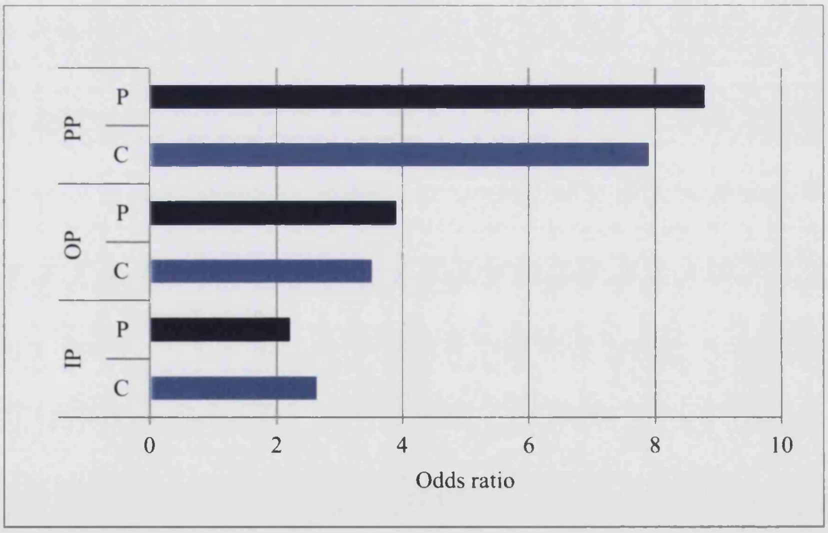
The impact of children on poverty can also be seen from the family structure variable for the general population. Relative to single-person households with no children, lone parent families have the greatest risk of belonging to each of the poverty trajectories of all family types. Other things equal, they are four times more likely to be permanently poor and over twice as likely to experience transient poverty (IP and OP) than to be never poor. Couples with children have a higher risk of moving into poverty (OR=1.9) than permanent poverty (OR=1.5). In couple families, it is possible that both parents work, which reduces the likelihood of permanent poverty. However, one parent may enter part-time/flexible work or drop out of the labour market in order to care for the children, which increase the risk of moving into poverty. There is no statistically significant effect of couples with children on experiencing a declining risk of poverty over time.

For children, lone parenthood has no significant effect on moving into poverty but has a more generalised effect on permanent and moving out of poverty by increasing the risk of trajectory group membership twofold. This is likely to be linked to employment status and the availability of child care.

Living in a workless household has a significant effect on all three trajectory groups for both samples and is the second largest risk factor for permanent poverty. Figure 7.5 shows that whilst children from workless households are less likely to experience permanent poverty than the general population (OR=7.9 versus 8.8), they have a greater likelihood of moving into poverty, and once poor, a lower likelihood of moving out compared with the population. An explanation why children from workless households have a lower likelihood of permanent poverty that the population is because of the targeting of social assistance support programs towards poor children from workless households, particularly after 1997 (see Table 1.1 for more details).

Having at least one adult in paid work but not all in the household has no effect on child poverty. In contrast, it increases the risk of moving into poverty by a quarter and permanent poverty by 40 per cent for the general population, which highlights that paid work *per se* is not enough to stave off poverty.

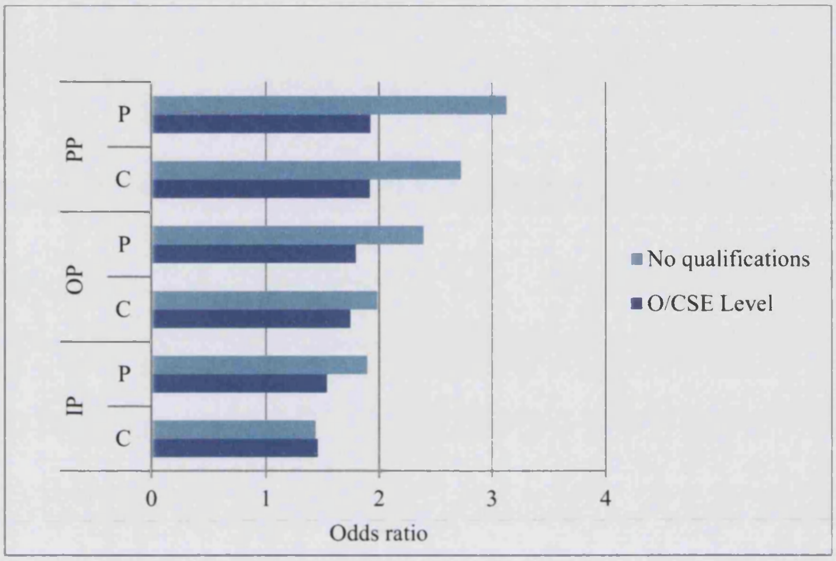
Figure 7.5: Odds ratios for the impact of no paid work on trajectory group membership



Source: Derived from the BHPS 1991-2002 unbalanced panel.
Odds ratios derived from tables 7.8 and 7.9 (other variables held constant).
OP=Moving out of poverty; IP=Moving into poverty; NP=never poor; PP=permanently poor
The reference category for the dependent variable is never poor. The reference category for the explanatory variable is all adults in paid work.

As expected, there is a gradient in the impact of education qualification on the probability of trajectory group membership, with the differential being the widest for permanent poverty (Figure 7.6). The effect of O/CSE level qualifications is similar for both samples and across trajectory groups, however, no qualifications has a larger impact on the population than on children. Education level of the head has a more general effect on the probability of children moving into poverty.

Figure 7.6: Odds ratios for the impact of a non-qualified head on trajectory group membership



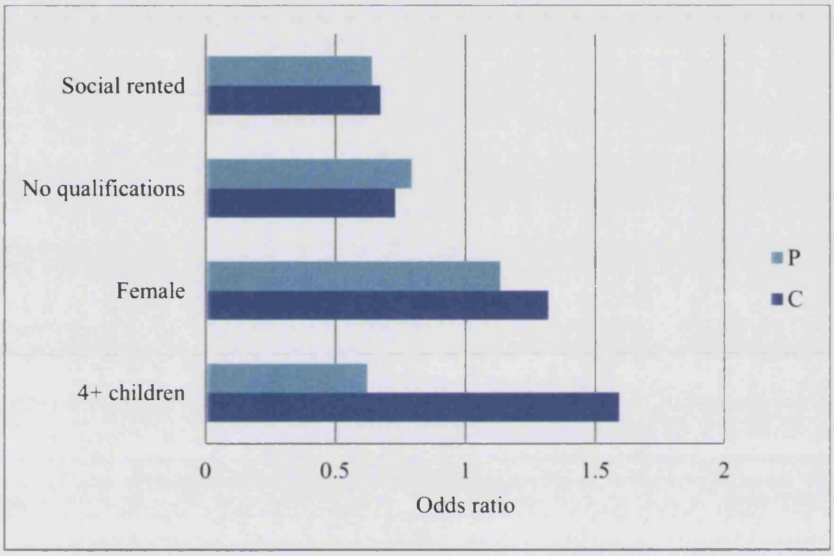
Source: Derived from the BHPS 1991-2002 unbalanced panel.
OP=Moving out of poverty; IP=Moving into poverty; NP=never poor; PP=permanently poor
The reference category for the dependent variable is never poor. The reference category for the explanatory variable is household head with A-Level or higher qualifications.

A positive finding from the regression analysis which confirms findings from the descriptive analysis is that individuals with the 'adverse' characteristics of living in social rented accommodation, belonging to a head with low or no qualifications, a lone parent, a household with no workers, and up to three children in the household had a greater probability of moving out of poverty than moving into poverty relative to the non-poor.

To ascertain whether there are any statistically significant differences in characteristics between the two transient groups, the moving in to poverty group is compared with the moving out of poverty group. Some of the effects are depicted in Figure 7.7. Whilst female headedness has no effect on the probability of belonging to any poverty trajectory group relative to the non-poverty group, it does significantly increase the risk of moving into poverty compared with moving out of poverty at the 10 per cent level for both samples. Furthermore, children living in social rented accommodation, belonging to a household head with no qualifications, or a lone parent are less likely to move into poverty than they are to move out of poverty. As expected, having three or more siblings statistically raises the likelihood of moving into poverty.

There are some notable differences between findings from both samples. Lone parenthood has no effect on moving into poverty, however, couple families with children are 1.7 times more likely than single person households to move into poverty than to move out. Having at least one paid worker in the household has no effect on children's likelihood of entering poverty, however, it increases the risk for all individuals by almost a fifth.

Figure 7.7: Odds ratios for the impact of selected variables on moving into poverty



Source: Derived from the BHPS 1991-2002 unbalanced panel.
All other variables held constant.
OP=Moving out of poverty; IP=Moving into poverty; NP=never poor; PP=permanently poor
The reference category for the dependent variable is moving out of poverty.

7.5.4 Predictions

In addition to examining the correlates of trajectory group membership via the different contrasts using multinomial logistic regressions, it is informative to estimate the predicted probabilities of trajectory group membership for persons with different combinations of characteristics.

The reference person, 'advantaged', is an individual from a couple family with two children (or, in the case of the children's sample, one sibling) who lives in privately owned accommodation, with all adults in paid work and no disabled or long-term sick people in the household. Furthermore, the household head is male, aged 26-34 and has at least A-Level qualifications. A sensitivity analysis is conducted by changing *ceteris paribus* each characteristic of the reference person. Finally, to assess the cumulative impact of a various adverse characteristics on trajectory group membership, predicted probabilities are also simulated by concurrently changing all of the characteristics ('disadvantaged' case).

The various predictions for children are summarised in Table 7.10 (and Table A7.6 in the Appendix for the population), and were derived using the point estimates of the parameters shown in tables 7.8 and 7.9. The shaded bars in each column depict the relative magnitude of the predicted probabilities within each trajectory class for a change in or accumulation of each characteristic.

Table 7.10: Predicted probabilities of trajectory group membership: children

Profile	OP	IP	PP	NP
1) Advantaged	0.07	0.05	0.03	0.84
2) Sex of head: Male → female	0.07	0.06	0.03	0.84
3) Tenure: Privately owned → social rented	0.17	0.08	0.09	0.66
4) Qualification of head: A-Levels or above → no qualifications	0.13	0.07	0.08	0.72
5) Parental status of head: Couple → lone	0.13	0.05	0.07	0.74
6) Age of head: 26-34 → <=25	0.07	0.08	0.04	0.80
7) Household employment status: All employed→ workless	0.18	0.09	0.17	0.55
8) Number of children: 2 → 4+	0.10	0.13	0.17	0.60
9) Non-disabled head → disabled head	0.07	0.05	0.04	0.84
10) N. LT sick: 0 → 2	0.09	0.04	0.03	0.83
11) Disadvantaged (accumulation of 2-10)	0.09	0.04	0.85	0.01

Source: Source: Derived from the BHPS 1991-2002 unbalanced panel.
OP=Moving out of poverty; IP=Moving into poverty; NP=never poor; PP=permanently poor

'Advantaged' cases from both samples have over an 80 per cent chance of never experiencing poverty, whereas the chance for 'disadvantaged' cases is negligible. On the whole, the predicted probabilities for a change in each single characteristic are similar for both samples, however, children with an accumulation of adverse risk factors are disproportionately more likely than all individuals to be permanently poor (0.85 versus 0.79) and less likely to move out of poverty (0.09 versus 0.14). For both samples, the cumulative impact of the risk factors on the probability of moving into poverty is relatively small for both samples.

A change from all adults being employed to workless and an increase in the number of children are the two biggest factors that increase the risk of permanent poverty for both samples (although the number of children has a larger effect on the children's sample). The effect is over twice as large as the change in the head having no qualification or being a lone parent.

The single biggest risk factor that influences the movement into poverty is an increase in the number of children in the household. Households with children are more likely to reduce their employment through parents reducing their working hours or moving to more flexible but lower paid jobs to fit in their child-rearing activities. Furthermore, children increase the burden on the household income.

In addition to employment status of the household, a change in tenure, education level of the head and parental composition are important factors that increase the probability of moving out of poverty relative to other trajectories. A move to social housing is likely to reduce living costs, thereby, increasing disposable income. Sex of the head, disability status of the head and the number of long-term sick have little impact on the predicted probability of trajectory group membership for both samples.

The bars highlight the stark effect of multiple disadvantage on the probability of poverty. A 'disadvantaged' child is 28 times more likely to be permanently poor compared with an 'advantaged' child. In contrast, an 'advantaged' child is 61 times more likely to be never poor than a 'disadvantaged' child.

Following the analysis of the incidence of an accumulation of factors for poor/non-poor individuals in Chapter 6, Figure 7.8 similarly breaks down the distribution of the number 'advantaged' or 'disadvantaged' characteristics within each trajectory class for children. [40] If the theory of cumulative disadvantage holds, it is expected that the proportion of permanently poor children is positively related with an increase in the 'disadvantaged' index and negatively related with an increase in the 'advantaged' index. The opposite is expected in the case of non-poor children. If the theory of democratisation holds, it is expected that both indices are less skewed towards the tails of the distributions and that PP and NP individuals have a combination of both.

The shapes of the distributions for the NP and PP groups follow the same patterns as those found for children who were non-poor and poor at *t* in Section 6.5.4. With regards to the sample of PP children, the shape of the distribution of both types of factors is similar (contrary to expectations), with the mode being 3 characteristics. 6 per cent of PP children have no adverse characteristics, whereas no children have all nine. There is an accumulation of risk factors but the index declines sharply after 5. 32 per cent of PP children have 4 or 5 negative risk factors, however a similar proportion (37 per cent) have 4 or 5 positive characteristics.

The distribution of the characteristics amongst the long-term non-poor children is distinctly different from that of PP children. 33 per cent have no 'disadvantaged' characteristics. The mode is 1 characteristic (42 per cent), with a sharp decline thereafter. The distribution of the 'advantaged' characteristics is skewed

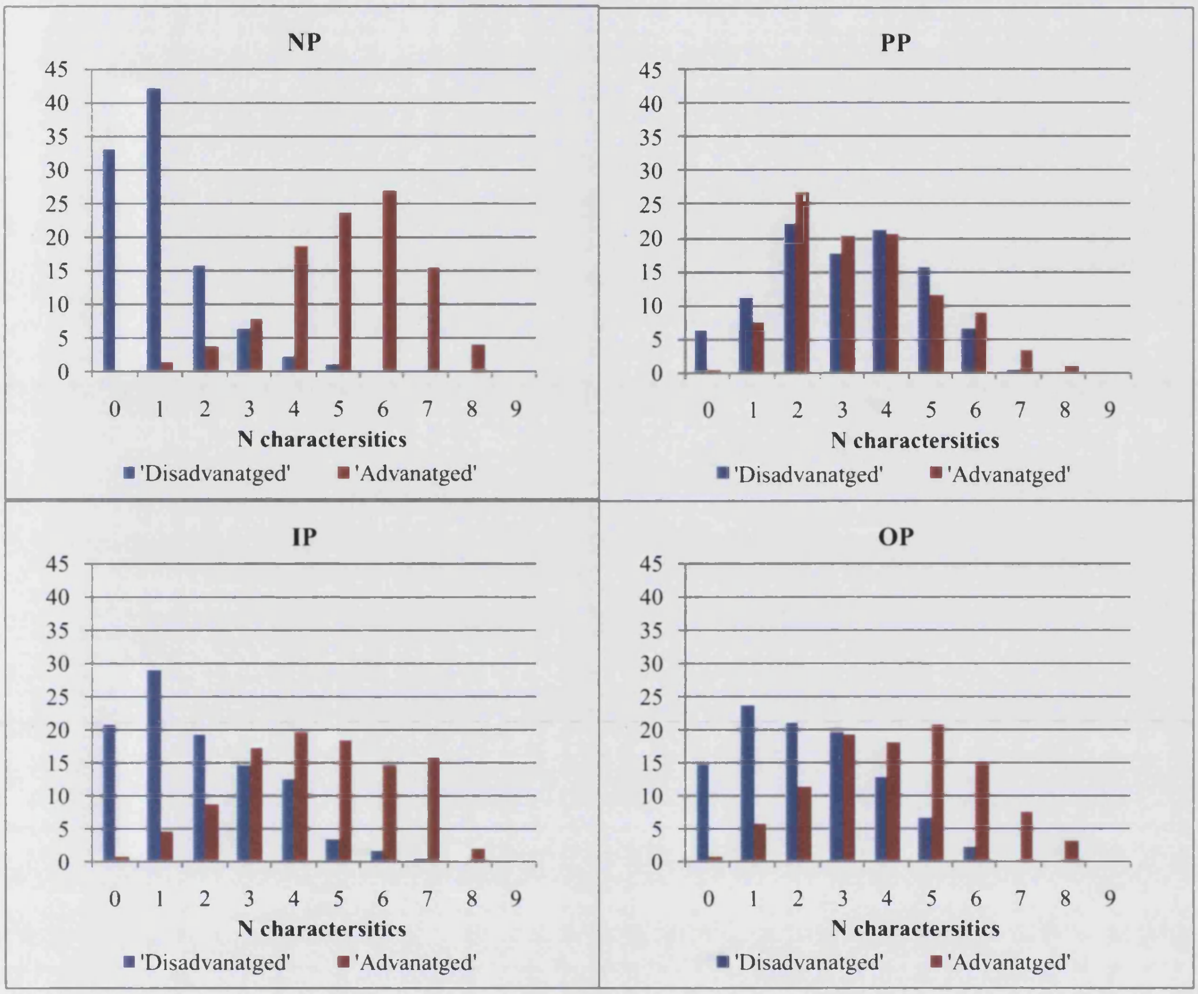
[40] See Section 6.5.4 for details.

towards the top end, with the mode being 6. No children have all nine factors but almost a fifth (19 per cent) have 8 or 9.

The two transient poor groups (IP and OP) share very similar shaped distributions for both indices. When the index is equal to at least 4, IP and OP groups are more likely to have 'advantaged' characteristics. Again, there is no evidence of cumulative disadvantage within these poor groups. Approximately 60 per cent of children have between 1 and 3 adverse characteristics. Thus, there is evidence of 'democratisation' amongst the transient poor: individuals with disadvantaged characteristics leave poverty, and those with advantaged characteristics move in to poverty.

These findings highlight that whilst the predicted probabilities show that cumulative disadvantage is a potential problem amongst the poor, the incidence estimates do not provide support for this hypothesis. Instead, all three poverty trajectories appear to be democratised: the data does not show that there are typical poverty profiles charactersised by marginalised groups. Instead, it extends more widely across society, if only temporarily, with a large proportion of IP, OP, and PP groups of children having several positive characteristics.

Figure 7.8: Distribution of 'advantaged' and 'disadvantaged' characteristics within trajectory groups: children



Source: Derived from the BHPS 1991-2002 unbalanced panel.
NP=never poor; PP=permanently poor; IP=Moving into poverty; OP=Moving out of poverty

7.6 Conclusion

This chapter proposes a new approach to assessing changes in children's risk of poverty over time. The analytic approach used, namely latent class growth analysis, assumes that the population is comprised of a mixture of groups characterised by different poverty histories. The existence of heterogeneous classes accords with the distinction that previous studies of dynamic poverty make between long-term, short-term and transitory poverty. LCGA offers several advantages. For example, it allows the statistical testing of whether longitudinal characterisations of poverty based on subjective rules represent true variation in the population. Secondly, it is possible to estimate the proportion of children who experience each of the derived poverty trajectories, and how the probability of poverty within each trajectory changes over time. Thirdly, LCGA allows one to test the strength of the relationship between trajectory membership and background variables, allowing an assessment of whether different characteristics have general or specific effects on children's patterns of poverty.

The research in this chapter also highlighted that the subjective approach based on spells of poverty and the LCGA approach are both fruitful and complementary. In the subjective approach, spells are independent of each other, therefore, it cannot elaborate upon how the risk of poverty within each group increases or decreases over time – only the size of each group. On the other hand, the LCGA approach cannot glean information on the level of poverty 'churning' (that is, short-term movements in and out of poverty) but can show how the probability of poverty changes over time within statistically validated trajectory groups. A limitation of placing too much emphasis on short-term movements is whether they represent genuine movements due to the presence of measurement error.

The analysis identified four trajectories of poverty for children and the general population. The first group, which is labeled the non-poor group, has a very low likelihood of experiencing poverty over time. In contrast, the second group, which is labeled as the permanent poor group, has a very high risk of experiencing poverty in any given year. The remaining two groups have variable risks of experiencing poverty over time. The third group, which is referred to as the moving out of poverty group, begins with a high risk of poverty, however, members eventually transition out of poverty over time. Finally, the fourth group, which is labeled as the moving into poverty group begins with a low probability of poverty, but over time, this probability rises. An encouraging finding was that children were more likely than all individuals to move out of poverty over time. The chapter also showed that particular findings were sensitive to the choice of the poverty line. For example, the proportion of people moving into poverty over time remained fairly stable across poverty line specifications however, the OP and PP groups increased in size as the threshold increased.

The findings from this chapter lend support to the *temporalisation* thesis of poverty by showing that the majority of people who experience poverty do not do so on a continuous basis. Instead a large proportion of individuals have transient experiences of poverty. These findings should not detract from the fact that a consistent finding across all three poverty thresholds is that children were more likely to suffer from permanent poverty than all individuals. This has important implications given that poverty in childhood is a forerunner to other disadvantages across the life-course.

Results from the examination of the determinants of group membership highlighted the unequal distribution of social groups across the different poverty trajectories. The results both supported findings from previous research on the determinants of poverty and simultaneously gleaned new insights into the nature of longitudinal poverty dynamics. Consistent with previous studies, it is found that children in larger families, with no paid workers, headed by lone parents, or household heads with no qualifications have a heightened risk of belonging to one of the poverty trajectories. Protective characteristics such as high levels of qualifications and employment are associated with belonging to the never poor group. Whilst this finding is expected, taking heterogeneity of poverty experiences into account shows that these factors do not necessarily guard against poverty. The findings also suggest that individuals belonging to the two transient groups have distinct characteristics, for example, individuals belonging to female headed households are more likely to move into poverty than to move out.

A valuable output from the analysis is that it is possible to ascertain which sub-groups of people improved their position over time. 'Disadvantaged' groups are not doomed to long-term poverty, for example, individuals belonging to heads who were workless, with no qualifications or to lone parents had a greater chance of moving out of poverty than moving in.

The simulation of predicted probability profiles showed that whilst an accumulation of risk factors raised the likelihood of permanent poverty, no actual cases were identified who had all adverse characteristics. Thus, there was little support for the 'cumulative disadvantage' hypothesis. Instead, all three poverty trajectories were characterised by multiple advantages, lending support for the 'democratisation' hypothesis.

Nagin and Tremblay (2005) and Nagin (2005) have cautioned against the reification of trajectory groups. Rather, the trajectory groups should be viewed as a statistical device to approximate and simplify a more complex underlying reality. Furthermore, although individuals are assigned to their 'most likely' trajectory groups based on posterior probabilities, they have a non-zero probability of belonging to other trajectory groups (as demonstrated in tables 7.4 and 7.5). Reification may also create the impression that the groups are immutable. However, length of the observation period and sample size can impact upon the number and shape of trajectories (Sampson, Laub and Eggleston, 2004). According to Nagin, *"...even though the past is prologue to the future, the past does not determine the future."* (Nagin (2005), p.p. 175). The addition of further waves of panel data will allow future studies to assess how poverty trajectories unfold over time.

Chapter 8 Conclusion

8.1 Introduction

The concluding chapter reviews the rationale and objectives of the thesis and highlights the key findings. Methodological considerations are then addressed, including the strengths and limitations of the research. This is followed by a discussion of the implications of the findings and suggestions for future research.

8.2 Recap of rationale and objectives

i. The context for the thesis is the Government's ambitious target to eradicate child poverty by 2020 with interim targets to reduce it by a quarter by 2004/05 and to halve it by 2010/11 compared with its level in 1998/99. Since 1998/99, there had been a sustained decline in child poverty, however, the Government failed to meet its first target and achieved a 21 per cent reduction in child poverty by 2004/05. Furthermore, child poverty began to rise in 2005/06 and 2006/07 despite the wide range of policy initiatives and increased investment in children. This suggests that the goal of halving child poverty by 2010/11 appears to be enormously challenging.

ii. The Government targets are being judged using static headcount measures of poverty. Static analyses can only highlight whether the number of poor people is greater or less than in previous years. The poor and non-poor are treated as mutually exclusive groups who do not escape these states, thus, it is not possible to ascertain whether those in poverty last year remained poor or escaped this condition. As a consequence, static measures take no account of whether children experience poverty over a number of years, and therefore, underestimate the extent of child poverty over time.

iii. While research on cross-sectional trends in child poverty and the associated risk factors is well established, there has been a dearth of research into the dynamic aspects of child poverty.

iv. Research into the dynamic aspects of child poverty is important since the longer the time a child spends in poverty, the more serious are the consequences to the quality of childhood, future outcomes across the life-course, and to society as a whole.

The primary objective of this thesis was to explore the heterogeneity of child poverty experiences using twelve annual waves of the British Household Panel Study (1991-2002). Low income was used as a proxy for poverty, with poverty defined as living in a household where income is below 60 per cent of the median adjusted for household size. Time in the mediation of poverty was explored across three distinct dimensions, namely, cross-sectional trends, short-term transitions between two consecutive years, and longer-term trajectories over the entire twelve year period. Children were systematically compared with the overall population in order to assess similarities, differences, and progress over time. As the poverty line is essentially arbitrary, the sensitivity of the findings are tested at different thresholds. Specific theoretical hypotheses (democratisation, temporalisation, and persistence) were tested to gauge the temporal nature of poverty.

8.3 Key findings

i. Trends

Chapter 4 analysed cross-sectional trends in poverty based on the Foster-Greer-Thorbecke class of indices (the headcount, poverty gap, and squared poverty gap indices). A number of positive findings emerged. Firstly, the largest improvement in the growth of incomes was experienced by children. Those with the lowest incomes made the largest gains, particularly after 1997. Secondly, progress has been made in reducing the relative differential between the population and child indices over time. The greatest convergence occurred at the 50 per cent of median income poverty line, which reflects the increase in incomes of the poorest children.

Despite this progress, children had persistently lower incomes than the population. This translated into children having higher headcount, poverty gap, and squared poverty gap indices than the population across the twelve years. Furthermore, the proportional reduction in the squared poverty gap was less than the reduction in the poverty gap. This in turn was smaller than the reduction in the headcount ratio. These findings suggest that it has been relatively easy to increase the incomes of children closest to the poverty line.

As poverty lines are arbitrary and the choice of indices for the measurement of poverty levels can give rise to different findings, stochastic dominance was undertaken to establish whether there had been an unambiguous reduction in poverty. The analysis confirmed this for a reasonable interval of poverty lines and across the FGT class of indices.

ii. Transitions

With regards to Chapter 5, the descriptive analysis showed that while poverty for the majority of individuals is not persistent, it is not necessarily a one-off experience. The findings show that many individuals who leave poverty return to experience recurrent episodes of poverty. The proportion of individuals who experience poverty at least once is approximately twice the average cross-sectional poverty rate. An explanation for this is that a large proportion of individuals who have exited poverty or have fallen into it have incomes near the poverty line. As a consequence, oscillation of incomes around the poverty line is high. A second explanation for the high level of poverty transitions is the presence of measurement error in the income data, which leads to an overstatement of mobility and an understatement of poverty persistence in the observed data.

It was hypothesised that a Markov model would be appropriate for characterising poverty mobility. After fitting several models that allowed for the presence of measurement error and heterogeneous chains, it was found that a latent Markov mover-stayer model provided the best fit to both the population and children's samples of data. The estimates from the model indicated considerable poverty mobility, with approximately half of all individuals and children belonging to the mover chain. Given the assumption of a Markov process, members of this chain experienced short episodes of poverty, either staying poor for two consecutive years, or entering or exiting it at $t+1$. Two groups of people belonged to the stayer chain, namely, those who are always poor or never poor. Only a small minority of individuals stayed poor throughout the twelve year period (3 per cent of all individuals and 4 per cent of children). It was also hypothesised that the presence measurement error is significant in poverty mobility data. The error-corrected estimates showed that observed transition probabilities were shown to exaggerate the magnitude of poverty mobility and under-state poverty persistence compared to latent transition probabilities. Thus, what appears to be transitions into or out of poverty is actually measurement error.

The trends in transition probabilities arsing from the latent Markov mover-stayer model showed that before 1997 children were more likely than the general population to enter poverty, and thereafter entry risks declined towards population levels. For the population, this risk remained fairly static throughout the twelve year period. The cross-sectional reduction in child poverty mirrors the decline in poverty entry over time. A finding that gives cause for concern is that the probability of children staying poor in two consecutive waves remained very high over the entire twelve year period (especially once measurement error had been accounted for) and was at the same level in 2001/2002 as a decade earlier. This was despite the reduction in cross-sectional child poverty rates. Thus, once poor, children were more likely to stay poor than to escape it the following year. Chapter 6 considered whether there are causal effects from past poverty experience on future poverty status. The results suggest that even after controlling for observed and unobserved differences, poverty in one year was significantly associated with an increased risk of poverty in the future.

iii. Trajectories

With regards to the analysis of longer-term trends, latent class growth analysis was used to ascertain whether a number of statistically significant distinct trajectories of poverty existed. Four trajectories were identified in which individuals were classified as never poor, always poor, or temporarily poor (moving into poverty and moving out of poverty). It was found that even from a long-term perspective, poverty appears to be a widely shared experience, with 44 per cent of children and 38 per cent of the population belonging to one of the three poverty trajectories. The vast majority of those who had a poverty experience did so on a temporary basis by either entering it after a period of non-poverty or overcoming it. Only a minority of individuals stayed constantly poor, which confirmed the finding in Chapter 5.

Children were more likely than the population to belong to the moving out of poverty trajectory and less likely to belong to the moving into poverty one. On the other hand, a negative finding was that children were less likely than the population to belong to the never poor trajectory and more likely to belong to the permanently poor one. An explanation for this is that children continued to have persistently lower incomes than the population despite the reduction in cross-sectional poverty.

The LCGA analysis showed that each trajectory was associated different risks. For example, whilst three-quarters of children in households where all adults or at least one adult were in paid work belonged to the never poor group, one in twelve children experienced permanent poverty and one in six children experienced transient poverty. A positive finding from the regression analysis is that children with the 'adverse' characteristics of living in social rented accommodation, belonging to a head with low or no qualifications, a lone parent, a household with no workers, and up to three children in the household had a greater probability of moving out of poverty than moving into poverty. This complements the findings from the cross-sectional analysis where the poverty rate for these groups declined proportionally more than for other groups of children.

Table 8.1 summarises the key findings in terms of the theoretical hypotheses, namely, democratisation, temporalisation, and persistence of poverty. The second column shows implied outcomes if the hypotheses were true, and the third column shows the actual findings from the thesis. Children shared the same short and long term longitudinal poverty patterns as the population, however, this finding is unsurprising given that children were assigned parental incomes. The research identified that important differences between both groups exist in the risk of experiencing particular patterns of poverty.

Taken together, the findings from the longitudinal analysis suggest a paradoxical characteristic of poverty dynamics, that is, poverty is simultaneously characterised by a large amount of *short-term* mobility, which lends support for the temporalisation hypothesis, due to individuals entering and exiting poverty over time, together with a small minority who experience uninterrupted episodes of *long-term* poverty, which lends some support for the persistence hypothesis. Democratisation of poverty was demonstrated through the heterogeneity of short- and long-term poverty patterns and by showing that traditionally 'protective' factors such as education and employment were not enough to stave off poverty.

Table 8.1: Summary of hypotheses and associated findings

Hypothesis	Implication of hypothesis if true	Findings
Democratisation Due to greater social and economic risks since in post-industrial societies, a greater number of people are at risk of experiencing poverty. Instead of being confined to clearly identifiable marginalised groups defined by traditional structural factors, poverty extends more widely into society.	**Chapter 5** If poverty is a more widely shared experience, it is expected that the proportion of individuals who experience poverty at least once is relatively high. All individuals do not share the same pattern of poverty dynamics over time. Instead, there is heterogeneity with respect to the experience of poverty mobility. **Chapter 6** Children with "favourable" characteristics are not immune to the experience of poverty. **Chapter 7** Individuals belonging to the poverty trajectory groups are heterogeneous with respect to their characteristics and those with "favourable" characteristics are not shielded from the experience of poverty.	**Chapter 5** The descriptive analysis showed that the probability of experiencing poverty at least once was high (and was greater for children than the population) and almost double the cross-sectional rate. The population is comprised of heterogeneous poverty experiences and can be described by a mixed Markov model with more than one chain. **Chapter 6** The analysis showed that a relatively high proportion of short-term persistently poor children were from households with all adults in employment, heads with at least A-Levels qualifications, and owned accommodation. **Chapter 7** Whilst three-quarters of children in households where all adults or at least one adult are in paid work belonged to the never poor group, one in twelve children experienced persistent poverty and one in six children experienced transient poverty (moving in or out of poverty). A similar pattern was evident for individuals belonging to heads to A-Level or higher qualifications.
Temporalisation As life courses have become increasingly individualised, poverty is no longer a fixed or long-term condition, but a temporary phase in the life-course.	**Chapter 5** A greater proportion of individuals experience short spells of poverty and relatively few longer, persistent spells. It is expected that the proportion of individuals belonging to the 'mover' chain is relatively larger than the proportion of poor individuals belonging to	**Chapter 5** Poverty was shown to be unlikely as a one-off event as the risk of reoccurrence in the future remains high. Estimates from the latent Markov model indicated considerable poverty mobility with approximately half of all individuals and children belonging

	the 'stayer' chain. **Chapter 7** It is expected that there are more than two distinct trajectories (that is, the never- and long-term poor) which include those whose risk of poverty increases and/or decreases over time.	to the mover chain. The Markov assumption implies that individuals experienced short episodes of poverty, either staying poor for two consecutive years, or entering or exiting it at t+1. **Chapter 7** Even from a longer-term perspective, poverty appeared to be a widely shared experience in the population. A relatively large proportion of individuals experienced a temporary stretch of poverty by either over-coming or entering it. In contrast, relatively few individuals experienced a permanent episode of poverty.
<u>Persistence</u> Certain groups of people are predisposed towards staying poor due to cultural, behavioural, or structural factors, which leads to downward spirals of deprivation. Persistence theories focus on the routes into poverty and not on the routes out. Thus, poverty is viewed as a long-term and largely static.	**Chapter 5** Persistent poverty can be characterised by the 'stayer' chain in which there are two groups who never experience poverty and those who always experience poverty. It is expected that the proportion of poor individuals belonging to the 'stayer' chain is relatively larger than the proportion of poor individuals belonging to the 'mover' chain. **Chapter 6** Persistent poverty is associated with an accumulation of adverse risk factors. **Chapter 7** It is expected that there are only two distinct and static trajectories – those who are always poor or never poor. Long-term persistent poverty is associated with an accumulation of adverse risk factors.	**Chapter 5** A very small minority of individuals stayed poor for the entire twelve years. Within the 'mover' chain 3.2 per cent of all individuals and 3.9 per cent of children were estimated to be constantly poor. **Chapter 6** The simulation of predicted probability profiles showed that each adverse characteristic raised the risk of poverty, however, there was very little evidence of children in the sample who actually had a large number of adverse characteristics. **Chapter 7** In addition to the never poor and always poor trajectories, two additional ones existed, that is, moving into and moving out of poverty. A minority of children (14 %) belonged to the long-term persistent poor group. As in Chapter 6, the simulation of predicted probability profiles showed that whilst an accumulation of risk factors raised

		the likelihood of permanent poverty, no actual cases were identified who had all adverse characteristics.

8.4 Strengths of the thesis

The main strength of the dynamic approach in this thesis is that it builds a richer picture of child poverty across different time dimensions. More specifically, it elicits heterogeneous patterns of poverty, an examination of which sub-groups of individuals have improved their position over time, and the processes that underlie poverty movements. Thus, the dynamic approach goes beyond looking at how many people are poor and how poverty is distributed in society but also considers the causes. The originality and specific methodological strengths of each empirical chapter are now considered.

Each empirical chapter provided a comprehensive literature review of the research methods and findings to date for poverty dynamics in the context of each of the time dimensions (cross-sectional, short-term transitions, and longer-term trajectories). This allowed for the statistical techniques adopted in this thesis to be justified in the light of existing research, and for the results to be discussed in the context of similar studies.

Chapter 4 advanced the literature on child poverty in two important ways. Firstly, it allowed the trends from the BHPS to be compared with those reported in the official annual HBAI series. Secondly, the HBAI publications provide no analysis of the "depth" and "severity" of income poverty, thus, it is unclear to what extent the poorest children have improved their economic position over time. This chapter partly fills this gap in knowledge.

The modelling of short-term poverty transitions in Chapter 5 had a number of strengths. Descriptive turnover tables are traditionally used to assess entry and exit probabilities between two time periods, however, these assume that the population is homogenous and that mobility rates can be averaged across the sample. Applying latent Markov models allows for the possibility of heterogeneity in mobility patterns. Secondly, to the author's knowledge, it is the first application of latent Markov models to the study of child poverty. This enables an assessment whether the process of and trends in transition probabilities are different for children relative to the population. Finally, the number of panel waves used in the current study is greater than in previous applications of this method, which allows an examination of how patterns of poverty transitions have changed over a longer time frame.

The use of a dynamic random effects model probit in Chapter 6 allowed an examination of the underlying causes of poverty persistence that went beyond simply considering observed characteristics. The inclusion of unobserved heterogeneity and state dependence allowed an assessment of the relative contribution of the three factors towards raw poverty persistence, each of which has different policy implications.

LCGA modelling in Chapter 7 allowed the statistical validation of distinctive poverty trajectories, which is in contrast to traditional descriptive methods based on counting the number of years or sequencing of episodes. Second, the technique makes it possible to estimate how the risk of poverty within each trajectory changes over time. Thirdly, the probability of trajectory membership can be related to individual and family characteristics, allowing the investigation of how different characteristics have different effects on children's patterns of poverty.

8.5 Limitations of the thesis

The dynamic approach used in this thesis has provided a richer account of the nature of child poverty, however, there are some general limitations to consider (in addition to the specific methodological limitations that were discussed in each empirical chapter).

The use of arbitrary poverty lines to distinguish who moves into and out of poverty treats the experience of an individual whose income was way above the poverty line but fell substantially below it as equal to an individual whose income was only slightly above and fell by a small amount. The movement into poverty for the former is likely to have had a significant impact on living standards compared with the latter. Chapter 5 highlighted that the creation of 'false events' is exacerbated by misclassification arising from measurement error.

The fundamental difference of the dynamic approach compared to the static approach is that the former requires longitudinal data in order to follow individual poverty trajectories over time. A natural consequence (and danger) of using longitudinal data is that it individualises poverty as measures of individual events or characteristics (such as unemployment, lone parenthood, divorce) are isolated as causes or triggers of poverty (Ellwood, 1998). However, this does not provide a full explanation given that individual outcomes are also influenced by wider exogenous forces such as the environment, economy, government policy, institutions, and neighbourhoods. Thus, influential covariates may exist that strengthen or weaken the findings or provide a clearer picture of poverty dynamics. This omitted variable bias arises mainly due to data limitations as household surveys tend not to record such macro-level variables. Caution is, therefore, warranted in the interpretation and use of findings from dynamic analyses that do not incorporate such factors.

Successive BHPS interviews were carried out approximately one year apart. A limitation with respect to the interpretation of the longitudinal findings is that it is not possible to ascertain whether changes in poverty status occurred between two discrete time points. Changes in poverty status may be more sporadic in nature due to fluctuating incomes throughout the year. As such, it not possible to distinguish between a long or continuing spell of poverty from numerous separate spells. Furthermore, there are limitations associated with the measure of poverty itself: the dichotomous variable does not take into account the distance of incomes from the poverty line.

8.6 Policy implications

This thesis is not designed to answer what kind of policies would be effective in reducing child poverty, however, each of the time dimensions that were considered point to particular implications for the Government's aim to abolish child poverty.

The findings suggest that it will be challenging to meet the Government's target to halve child poverty by 2010 and eradicate it by 2020 based on simple point-in-time headcount measures. The longitudinal nature of poverty may also provide a partial insight into why it failed to meet its interim target in 2004/05 of reducing child poverty by a quarter from its 1998/99 level.

An impression given by cross-sectional analyses of poverty is that the poor have undifferentiated experiences of poverty, however, the patterns identified from the longitudinal analysis do not accord with this either in the short or long term. There is a strong case for a targeted response towards different temporal patterns of poverty as the consequences of long episodes of child poverty are much greater than a one-off temporary episode. However, there are practical difficulties in identifying such groups of children. The findings highlighted that the risk factors associated with cross-sectional poverty are the same as those for longitudinal patterns of poverty (for example, worklessness, lone parents, a large number of children in the family). What differs is the strength of the association and accumulation of risk factors. Furthermore, the administrative process of assessing household incomes over a number of years or risk profiles would be intrusive, prone to error and resource-intensive.

The socio-economic correlates of poverty are well established, however, static headcount measures do not take into account the impact of state dependence and unobserved heterogeneity in increasing the risk of poverty. The existence of state dependence means that the experience of poverty itself increases the risk of experiencing it again regardless of observed and unobserved characteristics. Even if it is possible to target the currently poor precisely, a large proportion of children will move in and out of poverty between one year and the next. More worryingly, a large proportion of children who experience poverty in one year are more likely to stay poor the following year than exit it. Furthermore, most poverty transitions occur close to the poverty line. These findings imply that a slowdown in the progress in reducing child poverty since 2004/05 could be because of a lack of emphasis on *sustaining* exits out of poverty. Headcount based policies simply focus on lifting incomes above the poverty line in any one year, even if by one pound. Targeting the currently poor in any one year may involve wastage of resources given that many of the same individuals experience recurrent poverty. Early interventions that prevent children from becoming poor or encourage exits from poverty could have long-lasting benefits and reduce overall child poverty. Redistributive policies would need to seriously consider how much incomes need to increase to allow a sustained escape from poverty given that the findings indicate a high level of poverty reoccurrence due to incomes hovering close to the poverty line.

Given that a relatively large proportion of poverty persistence was explained by unobserved heterogeneity, policies aimed at breaking the "poverty trap" via monetary transfers to the poor may not be fully effective. Such policies may not be amenable to the adverse unobserved characteristics, thus, will not reduce the risks of experiencing poverty again in subsequent years. By definition, it is difficult to assess the precise nature of individual unobserved heterogeneity, therefore, it is challenging to accurately assess whether policy can affect this cause of poverty. However, research evidence from the cohort studies suggests that the effect of unobservable factors such as cognitive and non-cognitive traits have been shown to be increasingly important in explaining the decline of mobility in income between parents and their offspring as adults. The findings suggest that there needs to be greater targeting of education polices towards those from deprived backgrounds. Early interventions that focus on the development of personal skills could have long-lasting benefits by improving educational outcomes and future earnings potential, thereby reducing child poverty in subsequent generations.

Observed characteristics contributed around half the share of raw poverty persistence. In terms of policy implications, this suggests that it is important for policies to be directed at those characteristics that increase the risk of persistence

This thesis cannot provide a detailed analysis of the impact of anti-poverty policies since the Government's ambition to eliminate child poverty was declared, however, the evidence indicates a marked decline in child poverty among those groups who initially had the highest poverty rates. The descriptive and regression analyses support Government targeting of unemployment, help for households with a large number of children, lone parents, and heads with low levels of education to reduce child poverty. Although these groups have been specifically targeted by and benefited from recent welfare reform and anti-poverty policies, the cross-sectional and longitudinal analysis suggests large inequalities in the distribution of poverty across different sub-groups of children. Future policies also need to focus on reducing these disparities.

The cross-sectional and longitudinal findings endorse the Government's main strategy to fight child poverty through employment. It suggests, for example, that children in workless families are among those most vulnerable to short and long term persistent poverty. At the same time, it suggests that this group experienced greater than average reductions in the risk of point-in-time poverty and had a greater probability of moving out of poverty in the longer term. However, this is only part of the story as the findings also reveal that employment is not in itself sufficient to sustain a person above the poverty line. This explains why poverty has become a more temporalised phenomenon. The relatively large amount of poverty mobility and reoccurrence may indicate that a sizeable fraction of individuals do not have economic security from employment. Factors such as the type of employment (for example, full- or part-time), the prospect of job stability and retention given the growth in casual and temporary work, job progression, and scope for pay rises are also important factors for the risk of poverty rather than employment *per se*.

8.7 Suggestions for future research

The research considered the twelve year period from 1991 to 2002. The analysis can be replicated as additional waves of the BHPS become available. This would provide valuable insights about how poverty dynamics change with a longer time frame.

The study can be extended by considering the space dimension of poverty, that is, variations in poverty dynamics regionally, nationally, and cross-nationally to assess how the findings vary across different political, social, and economic contexts. For example, the ECHP could be used for a study of European child poverty dynamics and how different social protection systems explain cross-national variations in child poverty.

A more detailed exploration is required into the relationship between employment and poverty dynamics. This thesis only considered the numbers of employed adults in the household but future empirical work could analyse full-time versus part-time employment and status of employment (for example, level of skill, professional, manual).

This thesis used a limited definition of poverty, that is, low income. The study could be replicated using a broader set of indicators of poverty, such as, those related to direct measures of material deprivation (for example, housing deprivation) or subjective views of deprivation (for example, the ability to make ends meet). The advantage of using a wider set of indicators is that it will allow a more robust assessment of poverty dynamics by gauging where results overlap or differ.

Given the limitation of arbitrary poverty lines, a suggestion for future research is to analyse poverty dynamics using a more direct proxy for poverty, for example, social assistance receipt. This would eliminate the issue of non-equivalence of distance above/below the poverty line as someone is either in receipt of benefits or not.

The importance of longitudinal approaches in the analysis of poverty is increasing with the availability of panel data. The findings from Chapter 5 highlighted that measurement error can distort estimates on poverty transition rates by masking true change with spurious change. Greater research is required in the use of validation data to examine more closely the nature of the measurement error process, and thus, to apply adjustments to transition rates. Further research could also investigate what magnitude of income deviation around the poverty line would be considered a "true" or statistically significant movement over and above noise.

Heterogeneity in Chapter 5 was taken to mean the different underlying processes of poverty mobility over time rather than differences arising from observed or unobserved individual characteristics. Future research could stratify the analysis by sub-groups, for example, education level, employment status, or gender of the household head. Finally, both observed and error-corrected estimates showed that the majority of individuals who experienced poverty at t were more likely to remain poor the following year than to exit it. Further research is required to establish why poverty persistence has been so high and fairly static since 1991. This could be achieved by investigating the relationship between poverty persistence and a greater number of categories in the poverty indicator to denote how far income falls below the poverty line (i.e., the depth of poverty).

Unobserved individual heterogeneity was shown to be an important determinant of poverty. Further research is required to understand what types of unobserved characteristics or traits affect poverty. This is particularly important for the alleviation of child poverty since initial disadvantages can impact upon people's beliefs about their ability to change their own circumstances. Research could, for example, look at the role of aspirations in shaping future outcomes. Furthermore, Table 5.3 found that those with the very lowest incomes had the highest level of income immobility compared with others with incomes below the poverty line. Further investigation is required into the unobserved characteristics of this group of people in addition to the permanently poor group identified in Chapter 7.

The Labour government introduced Sure Start programs in disadvantaged areas to support families with young children in order to enhance the physical, social and intellectual development of young children through free pre-school education. Research by Esping-Andersen (2009) has emphasised the highest rates of return to skill investments are in the 0-6 age ranges. After this, returns decline exponentially. It would be useful to investigate whether benefits of such programs accrued to poor children and the impact of the development of cognitive and non-cognitive skills on poverty.

With regards to Chapter 7, a limitation of the LCGA analysis is that it only considered the value of correlates of the poverty trajectories at the initial time period. Future research could analyse whether events that occur *during* the course of the poverty trajectories alter the trajectories themselves. Such events could include life events such as changes in family structure, occupational mobility or the onset of illness of household members. Another possibility is to assess the impact of government policies on poverty trajectories, such as changes in welfare benefits or the provision of childcare for lone parents. This chapter considered the antecedents to poverty trajectory membership, however, as the availability of further panel waves becomes available, it may be possible to analyse how trajectory group membership in childhood is related to distal outcomes in the teenage years and young adulthood, for example, education achievement, health, employment status, and crime.

Future research could also consider the impact of important interaction effects between variables on poverty and how these effects have changed over time. Important interactions, for example, are lone parenthood and employment status, and education status and sex of the head. Appropriate statistical techniques for investigating this include hierarchical log-linear or logistic regression modelling.

8.8 Summary

The dynamic approach to poverty provides a richer set of analytical tools for understanding poverty. It highlights that escaping poverty is not simply about raising incomes above a threshold, even marginally, in a single year. Instead, poverty is a temporal phenomenon subject to people's changing circumstances. Only through longitudinal analysis is it possible to identify heterogeneous groups that would not have been revealed by the static approach. The findings highlight that the Government's target to abolish child poverty based on the static headcount measure will be challenging and inherently undermined without policies that recognise the complexity of poverty dynamics over time. Furthermore, the goal implies a long-term policy commitment, which will be aided if there is a greater understanding of the underlying causal processes leading to different experiences of poverty over time. This thesis has sought to identify some of these. The analysis has been wide ranging, with each empirical chapter progressing the findings by expanding upon the definition of time. The aim of this was to build a richer and more truthful picture of the dynamics of child poverty.

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Appendix A: Supplementary Tables and Figures

Chapter 3

Table A3.1: BHPS sample sizes

Year	Number of households	Total number of individuals	Number of children	% of children
1991	5538	11633	2852	24.52
1992	5227	11001	2611	23.73
1993	5228	10475	2541	24.26
1994	5125	10477	2520	24.05
1995	5034	10128	2433	24.02
1996	5066	10544	2527	23.97
1997	5027	10556	2474	23.44
1998	5007	10384	2448	23.57
1999	4974	10143	2368	23.35
2000	4916	10034	2395	23.87
2001	4887	9842	2351	23.89
2002	4853	9526	2270	23.83
Total	60882	124743	29790	23.90

Source: Derived from the BHPS 1991-2002

Table A3.2: Poverty lines (£/week): various fractions of median income, 1991-2002

	Fraction of median income		
Year	50%	60%	70%
1991	131.14	157.37	183.60
1992	137.41	164.90	192.38
1993	142.09	170.51	198.93
1994	141.44	169.73	198.02
1995	146.42	175.71	204.99
1996	151.50	181.80	212.10
1997	156.47	187.77	219.06
1998	159.54	191.45	223.36
1999	162.24	194.69	227.14
2000	168.73	202.48	236.23
2001	165.46	198.55	231.64
2002	169.55	203.46	237.37

Source: Derived from the BHPS 1991-2002

Chapter 4

Table A4.1: Definitions of the covariates

Variable	Description
Dependent variable	
Poor	1 if income is below 50%, 60%, or 70% of the median houehold income in current year, 0 otherwise
Sex of the head	
Female	1 if household head is female, 0 otherwise
Accommodation	
Owned	1 if living in owned accomodation, 0 otherwise
Social rented	1 if living in social rented accomodation, 0 otherwise
Private rented	1 if living in privately rented accomodation, 0 otherwise
Highest qualification of head	
A'-Levels or higher	1 if head has 'A'-Levels or higher qualifications, 0 otherwise
O/CSE Level	1 if head has O/CSE Level (or equivalent) qualifications, 0 otherwise
No qualifications	1 if head has no qualifications or highest level of education is primary, 0 otherwise
Family type	
Lone	1 if only one adult present in the household, 0 otherwise
Age of head	
Age <=25	1 if age of household head is below 26, 0 otherwise
Age 26-34	1 if age of household head between 26 and 34, 0 otherwise
Age 35-44	1 if age of household head between 35 and 44, 0 otherwise
Age 45+	1 if age of household head is above 45, 0 otherwise
Number of workers in the household	
All adults in paid work	1 if all adults in the household are in paid work, 0 otherwise
At least 1 paid worker but not all	1 if at least one adult but not all in the household is in paid work, 0 otherwise
No paid workers	1 if no adults in the household are in paid work, 0 otherwise
Number of siblings	
0 siblings	1 if child has no siblings, 0 otherwise
1 sibling	1 if child has 1 sibling, 0 otherwise
2 siblings	1 if child has 2 siblings, 0 otherwise
3+ siblings	1 if child has at least 3 siblings, 0 otherwise
Disability status of head	
Disabled	1 if household head is disabled, 0 otherwise
Number of long-term sick	Number of long-term sick in the household

Source: Author
For the population, family type includes the categories pensioner single, pensioner couple, couple with children, couple with no children, single with children, and single with no children. It also includes a variable for the total number of children in the household, which ranges from 0 to 4+.

Table A4.2: Variable means and standard deviations 1991-2002, population

Variable	Mean	S.D.
Sex of the head		
Female	0.540	0.498
Accommodation		
Owned	0.719	0.449
Social rented	0.195	0.396
Private rented	0.086	0.280
Highest qualification of head		
A'-Levels or higher	0.459	0.498
O/CSE Level	0.315	0.464
No qualifications	0.226	0.418
Family type		
Pensioner single	0.076	0.265
Pensioner couple	0.080	0.272
Couple with children	0.080	0.272
Couple with no children	0.212	0.409
Single with children	0.070	0.256
Single with no children	0.158	0.365
Age of head		
Age <=25	0.076	0.265
Age 26-34	0.281	0.450
Age 35-44	0.262	0.440
Age 45+	0.381	0.486
Number of workers in the household		
All adults in paid work	0.570	0.495
At least 1 paid worker but not all	0.136	0.343
No paid workers	0.294	0.456
Number of children		
0	0.496	0.500
1	0.168	0.374
2	0.214	0.410
3	0.092	0.289
4+	0.030	0.170
Disability status of head		
Disabled	0.049	0.215
Number of long-term sick	0.189	0.645
N	124373	

Source: Derived from the BHPS 1991-2002
Unbalanced sample

Table A4.3: Variable means and standard deviations 1991-2002, children

Variable	Mean	S.D.
Sex of the head		
Female	0.571	0.495
Accommodation		
Owned	0.690	0.463
Social rented	0.245	0.430
Private rented	0.065	0.246
Highest qualification of head		
A'-Levels or higher	0.463	0.499
O/CSE Level	0.380	0.485
No qualifications	0.157	0.364
Parental type		
Lone	0.183	0.387
Age of head		
Age <=25	0.041	0.199
Age 26-34	0.319	0.466
Age 35-44	0.462	0.499
Age 45+	0.177	0.382
Number of workers in the household		
All adults in paid work	0.609	0.488
At least 1 paid worker but not all	0.197	0.398
No paid workers	0.193	0.395
Number of siblings		
0 siblings	0.268	0.443
1 sibling	0.434	0.496
2 siblings	0.219	0.414
3+ siblings	0.079	0.270
Disability status of head		
Disabled	0.027	0.163
Number of long-term sick	0.221	0.684
N	29790	

Source: Derived from the BHPS 1991-2002
Unbalanced sample

Chapter 5

Figure A5.1: Observed and error-corrected poverty persistence probabilities: 50 % poverty line

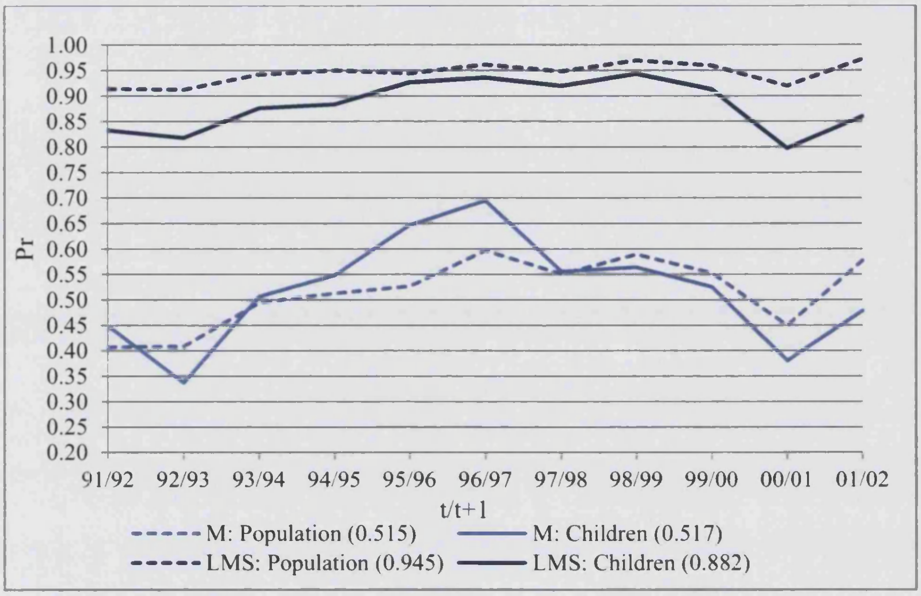
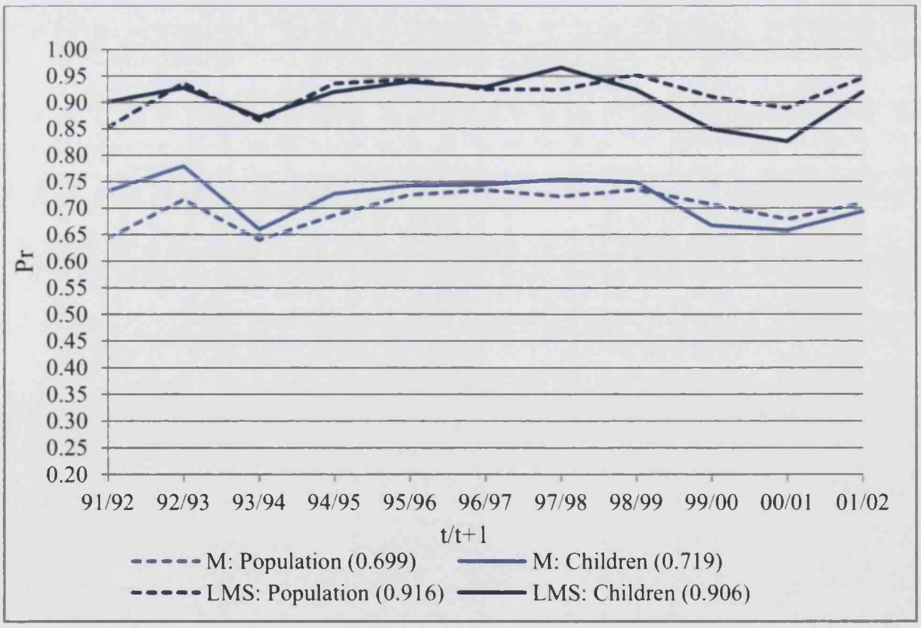


Figure A5.2: Observed and error-corrected poverty persistence probabilities: 70 % poverty line



Source: Derived from parameters in tables A5.5 and A5.6 for the observed Markov (M) probabilities, and tables A8 and A9 for the error-corrected latent Mover-Stayer (LMS) probabilities.
LMS probabilities are based on weighted sum of mover and stayer chains.
Figures in brackets denote average transition probabilities over the entire period.

Figure A5.3: Observed and error-corrected poverty entry probabilities: 50 % poverty line

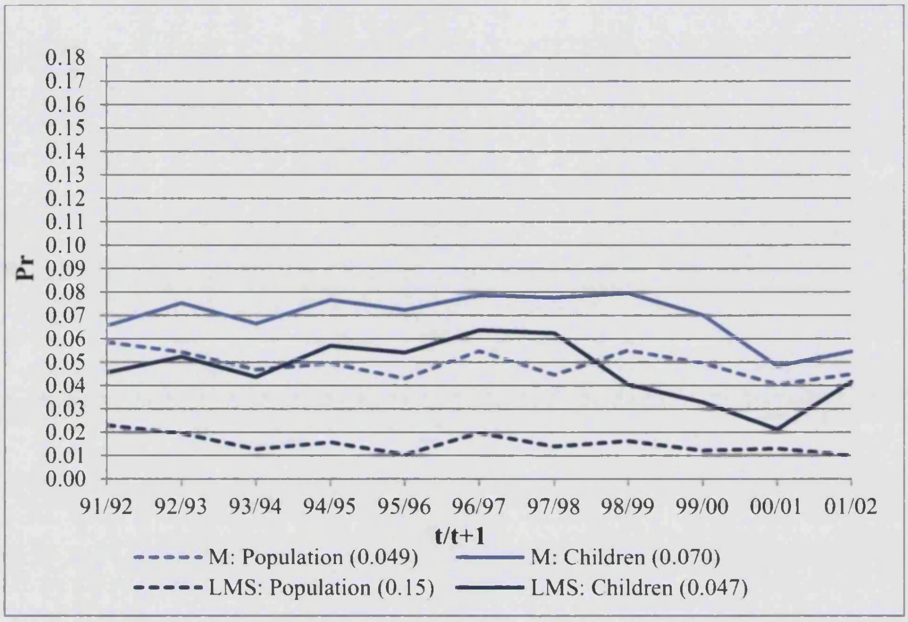
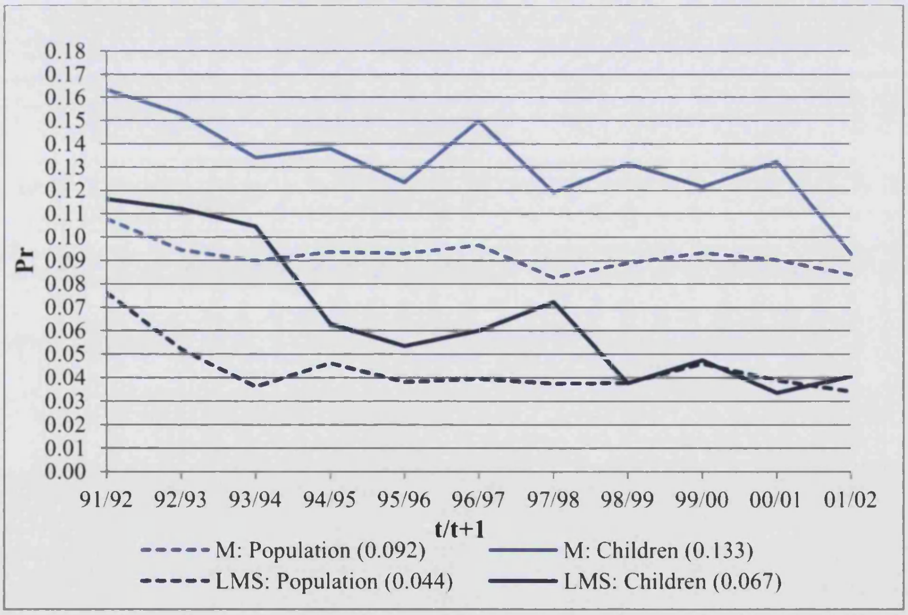


Figure A5.4: Observed and error-corrected poverty entry probabilities: 70 % poverty line



Source: Derived from parameters in tables A5.5 and A5.6 for the observed Markov (M) probabilities, and tables A8 and A9 for the error-corrected latent Mover-Stayer (LMS) probabilities.
LMS probabilities are based on weighted sum of mover and stayer chains.
Figures in brackets denote average transition probabilities over the entire period.

Table A5.1: Outflow rates (%) from wave *t* income group origins to wave *t+1* income

Income group at wave *t*	Income group, wave *t+1*													
	>0, <=10	>10, <=20	>20, <=30	>30, <=40	>40, <=50	>50, <=60	>60, <=70	>70, <=80	>80, <=90	>90, <=100	>100, <=120	>120, <=160	>160	Total
>0, <=10	**23.8**	10.9	1.6	10.9	11.9	4.2	9.3	2.6	5.7	4.7	5.2	4.2	5.2	100
>10, <=20	10.9	**6.9**	4.0	16.8	12.9	11.4	8.4	5.9	6.4	4.0	5.0	4.5	3.0	100
>20, <=30	1.5	3.7	**10.7**	16.3	15.8	11.4	10.7	7.1	7.1	5.1	5.8	2.0	2.9	100
>30, <=40	0.6	2.3	5.1	**24.7**	23.0	12.2	9.3	5.3	4.3	3.5	4.0	3.3	2.5	100
>40, <=50	0.8	0.9	2.5	10.8	**34.8**	16.9	11.1	7.5	4.9	2.5	2.4	3.2	1.9	100
>50, <=60	0.2	1.0	1.3	5.0	14.7	**33.5**	18.8	9.2	5.7	2.4	3.8	2.3	1.9	100
>60, <=70	0.4	0.6	0.6	2.0	6.6	17.2	**30.9**	15.2	11.5	4.6	5.5	3.3	1.6	100
>70, <=80	0.2	0.5	1.2	1.9	4.2	7.3	16.6	**27.5**	16.3	8.9	8.4	4.7	2.5	100
>80, <=90	0.0	0.2	0.8	1.0	2.0	4.9	8.6	17.0	**27.4**	16.2	13.4	6.2	2.4	100
>90, <=100	0.3	0.2	0.4	0.6	1.7	2.6	4.8	8.0	16.6	**25.7**	24.1	11.5	3.4	100
>100, <=120	0.2	0.3	0.3	0.7	1.6	1.9	2.7	5.0	6.5	13.3	**37.7**	23.9	6.1	100
>120, <=160	0.2	0.1	0.3	0.6	0.8	0.8	1.5	2.2	3.0	4.6	18.1	**49.8**	18.1	100
>160	0.2	0.1	0.1	0.3	0.5	0.6	0.8	1.1	1.0	1.9	4.6	16.9	**71.7**	100
	0.38	0.47	0.8	2.4	5.12	6.49	7.66	7.77	8.11	7.9	14.25	18.6	20.05	100

Source: Derived from the BHPS 1991-2002.
Note : balanced sample of all individuals
Transition rates are average rates from pooled waves of BHPS data

Table A5.2: Fit statistics for the independence model

	G^2	Dissimilarity Index	BIC
1) Population	17273.04 (p=0.000)	0.48	46350.35
1) Children	4797.55 (p=0.000)	0.39	12626.06

Introduce Markov assumption

Table A5.3: Fit statistics for the observed and latent Markov model (*S=1)*

		Observed			**Latent**		
		G^2	Dissimilarity Index	BIC	G^2	Dissimilarity Index	BIC
Population	*2)* Stationary	6191.23 (p=0.000)	0.29	35288.61	*6)* 3899.84 (p=0.322)	0.16	33027.66
	3) Non-stationary	6118.92 (p=0.000)	0.29	35184.55	*7)* 3841.16 (p=0.853)	0.29	35184.55
Children	*2)* Stationary	2263.61 (p=0.000)	0.30	10125.87	*6)* 1729.25 (p=0.223)	0.20	9625.18
	3) Non-stationary	2220.27 (p=0.000)	0.28	10029.06	*7)* 1705.56 (p=0.612)	0.20	9508.707

Introduce population heterogeneity

Table A5.4: Fit statistics for the observed and latent mixed Markov model (*S=2)*

		Observed			**Latent**		
		G^2	Dissimilarity Index	BIC	G^2	Dissimilarity Index	BIC
Population	*4)* Stationary	4489.77 (p=0.006)	0.15	33786.66	*8)* 3409.98 (p=0.713)	0.11	32749.12
	5) Non-stationary	4415.4 (p=0.039)	0.15	33525.08	*9)* 3344.26 (p=0.957)	0.11	32478.89
Children	*4)* Stationary	1855.3 (p=0.000)	0.18	9929.08	*8)* 1638.86 (p=0.374)	0.16	9696.81
	5) Non-stationary	1729.25 (p=0.013)	0.18	9698.47	*9)* 1595.00 (p=0.786)	0.16	9460.37

Source: Derived from the BHPS, 1991-2002

Table A5.5: Non-stationary manifest Markov parameter estimates, population

$$P_{x_{91}x_{92}\ldots x_{02}} = \delta_{x_{91}} \tau_{x_{92}|x_{91}} \tau_{x_{93}|x_{92}} \ldots \tau_{x_{02}|x_{01}}$$

		Initial Probabilities $\hat{\delta}_{x_{91}}$	
		Poor	**Not-Poor**
		0.1547	0.8453
		(0.0054)	(0.0054)
t		**Transition Probabilities $\hat{\tau}_{t+1,t}$** **t+1**	
		Poor	**Not-Poor**
1991	Poor	0.574	0.427
		(0.0189)	(0.0189)
	Not-Poor	0.078	0.923
		(0.0044)	(0.0044)
1992	Poor	0.555	0.445
		(0.0190)	(0.0190)
	Not-Poor	0.077	0.923
		(0.0043)	(0.0043)
1993	Poor	0.588	0.412
		(0.0190)	(0.0190)
	Not-Poor	0.074	0.926
		(0.0043)	(0.0043)
1994	Poor	0.597	0.403
		(0.0189)	(0.0189)
	Not-Poor	0.070	0.930
		(0.0042)	(0.0042)
1995	Poor	0.629	0.371
		(0.0187)	(0.0187)
	Not-Poor	0.068	0.932
		(0.0041)	(0.0041)
1996	Poor	0.673	0.327
		(0.0181)	(0.0181)
	Not-Poor	0.075	0.925
		(0.0043)	(0.0043)
1997	Poor	0.651	0.349
		(0.0176)	(0.0176)
	Not-Poor	0.070	0.930
		(0.0042)	(0.0042)
1998	Poor	0.654	0.346
		(0.0175)	(0.0175)
	Not-Poor	0.070	0.930
		(0.0042)	(0.0042)
1999	Poor	0.673	0.327
		(0.0172)	(0.0172)
	Not-Poor	0.070	0.931
		(0.0042)	(0.0042)

2000	Poor	0.557 (0.0181)	0.443 (0.0181)
	Not-Poor	0.061 (0.0039)	0.939 (0.0039)
2001	Poor	0.637 (0.0189)	0.363 (0.0189)
	Not-Poor	0.071 (0.0042)	0.929 (0.0042)

Source: Derived from BHPS 1991-2002
Standard errors in parentheses
N=4441

Notation

t=12 annual measurement points (1991 to 2002)

$\hat{\delta}_{x_{91}}$ is the observed proportion of the sample who are poor or not-poor at $t=1$.

$\hat{\tau}_{t+1,t}$ are observed transition probabilities between consecutive time points.

Table A5.6: Non-stationary manifest Markov parameter estimates, children

$$P_{x_{91}x_{92}\ldots x_{02}} = \delta_{x_{91}} \tau_{x_{92}|x_{91}} \tau_{x_{93}|x_{92}} \ldots \tau_{x_{02}|x_{01}}$$

		Initial Distribution $\hat{\delta}_{x_{91}}$	
		Poor	**Not-Poor**
		0.1919 (0.0118)	0.8081 (0.0118)
t		**Transition Probabilities $\hat{\tau}_{t+1,t}$** **t+1**	
		Poor	**Not-Poor**
1991	Poor	0.599 (0.0327)	0.401 (0.0327)
	Not-Poor	0.118 (0.0108)	0.882 (0.0108)
1992	Poor	0.591 (0.0320)	0.409 (0.0320)
	Not-Poor	0.103 (0.0104)	0.897 (0.0104)
1993	Poor	0.597 (0.0334)	0.403 (0.0334)
	Not-Poor	0.106 (0.0103)	0.894 (0.0103)
1994	Poor	0.556 (0.0333)	0.444 (0.0333)
	Not-Poor	0.088 (0.0090)	0.912 (0.0090)
1995	Poor	0.596 (0.0353)	0.404 (0.0353)
	Not-Poor	0.095 (0.0097)	0.905 (0.0097)
1996	Poor	0.663 (0.0333)	0.337 (0.0333)
	Not-Poor	0.090 (0.0095)	0.910 (0.0095)
1997	Poor	0.586 (0.0336)	0.414 (0.0336)
	Not-Poor	0.078 (0.0090)	0.923 (0.0090)
1998	Poor	0.615 (0.0348)	0.385 (0.0348)
	Not-Poor	0.071 (0.0085)	0.929 (0.0085)
1999	Poor	0.627 (0.0356)	0.373 (0.0356)
	Not-Poor	0.079 (0.0089)	0.921 (0.0089)

2000	Poor	0.540 (0.0363)	0.460 (0.0363)
	Not-Poor	0.071 (0.0085)	0.929 (0.0085)
2001	Poor	0.581 (0.0382)	0.419 (0.0382)
	Not-Poor	0.079 (0.0088)	0.921 (0.0088)

Source: Derived from BHPS 1991-2002
Standard errors in parentheses
N=519

Notation

t=12 annual measurement points (1991 to 2002)

$x_{91}, x_{92}, \ldots, x_{02}$ =observed poverty status (poor or not-poor)

$\hat{\delta}_{x_{91}}$ is the observed proportion of the sample who are poor or not-poor at $t=1$.

$\hat{\tau}_{t+1,t}$ are observed transition probabilities between consecutive time points.

Table A5.7: Non-stationary latent Markov Mover-Stayer parameter estimates, population

$$P_{x_{91}x_{92}..x_{02}} = \sum_{s=1}^{S}\sum_{a=1}^{A}\sum_{b=1}^{B}...\sum_{l=1}^{L}\pi_s\delta_{a|s}\rho_{s,x_{91}|a}\tau_{s,b|a}\rho_{s,x_{92}|b}\tau_{s,c|b}...\rho_{s,x_{02}|l}\tau_{s,k|l}$$

	Chain S	**Movers $s=1$**		**Stayers $s=2$**	
	Chain Proportion $\hat{\pi}_s$	0.469 (0.0127)		0.531 (0.0127)	
		Class 1	**Class 2**	**Class 1**	**Class 2**
	Initial distribution $\hat{\delta}_{a\|s}$	0.268 (0.0118)	0.732 (0.0118)	0.06 (0.0038)	0.94 (0.0038)
		Latent transition probabilities $\hat{\tau}_{s,latent_{t+1}\|latent_t}$			
		t+1			
t *Latent variable at t*		**Class 1**	**Class 2**	**Class 1**	**Class 2**
1991 *a*	**Class 1**	0.741 (0.032)	0.259 (0.032)	1	0
	Class 2	0.110 (0.012)	0.890 (0.012)	0	1
1992 *b*	**Class 1**	0.723 (0.028)	0.277 (0.028)	1	0
	Class 2	0.095 (0.010)	0.905 (0.010)	0	1
1993 *c*	**Class 1**	0.753 (0.026)	0.247 (0.026)	1	0
	Class 2	0.070 (0.009)	0.930 (0.009)	0	1
1994 *d*	**Class 1**	0.818 (0.025)	0.182 (0.025)	1	0
	Class 2	0.088 (0.009)	0.912 (0.009)	0	1
1995 *e*	**Class 1**	0.806 (0.023)	0.194 (0.023)	1	0
	Class 2	0.060 (0.008)	0.940 (0.008)	0	1
1996 *f*	**Class 1**	0.885 (0.021)	0.115 (0.021)	1	0
	Class 2	0.073 (0.009)	0.927 (0.009)	0	1

1997	**Class 1**	0.810 (0.023)	0.190 (0.023)	1	0
g	**Class 2**	0.080 (0.009)	0.920 (0.009)	0	1
1998	**Class 1**	0.833 (0.022)	0.167 (0.022)	1	0
h	**Class 2**	0.073 (0.009)	0.927 (0.009)	0	1
1999	**Class 1**	0.890 (0.021)	0.110 (0.021)	1	0
i	**Class 2**	0.058 (0.009)	0.942 (0.009)	0	1
2000	**Class 1**	0.864 (0.025)	0.136 (0.025)	1	0
j	**Class 2**	0.053 (0.008)	0.947 (0.008)	0	1
2001	**Class 1**	0.884 (0.030)	0.116 (0.030)	1	0
k	**Class 2**	0.053 (0.011)	0.947 (0.011)	0	1
		Response probabilities $\hat{\rho}_{s,manifest|latent}$			
		Poor	**Non-poor**	**Poor**	**Non-poor**
	Class 1	0.799 (0.010)	0.201 (0.010)	0.909 (0.013)	0.091 (0.013)
	Class 2	0.061 (0.004)	0.939 (0.004)	0.008 (0.002)	0.992 (0.002)

Source: Derived from the BHPS 1991-2002
Standard errors in parentheses
N=4441

Notation

S=2 is the number of chains in the mixed Markov Mover-Stayer model

$\hat{\pi}_s$ is the proportions of the sample in each of the *s* chains

$x_{91}, x_{92}, \ldots, x_{02}$ = observed poverty status (poor or not-poor)

$\hat{\delta}_{a|s}$ is the probability that a respondent belongs to one of A true latent classes at t=1 conditional upon membership in Markov chain *s*

a=1,...,A, b=1,...,B, ..., l=1,...,L are the twelve latent variables each with 2 classes corresponding to poverty/non-poverty at each of the twelve time points.

$\hat{\tau}_{s,latent_{t+1}|latent_t}$ are the transition probabilities between latent variables within each chain. Thus, $\hat{\tau}_{s,b|a}$, is the probability of belonging to class b $(b=1,2)$ at time point 2, given membership in class a at time point 1 and chain s. Stayers remain in their original class with a probability of 1.

$\hat{\rho}_{s,manifest|latent}$ are the conditional response probabilities and give the relationship between the observed variables and their latent counterparts for each chain. Deviations of the response matrix from identity give the degree of measurement error.

Table A5.8: Non-stationary latent Markov Mover-Stayer parameter estimates, children

$$P_{x_{91}x_{92}..x_{02}} = \sum_{s=1}^{S}\sum_{a=1}^{A}\sum_{b=1}^{B}\cdots\sum_{l=1}^{L}\pi_s\delta_{a|s}\rho_{s,x_{91}|a}\tau_{s,b|a}\rho_{s,x_{92}|b}\tau_{s,c|b}\cdots\rho_{s,x_{02}|l}\tau_{s,k|l}$$

	Chain S	Movers $s=1$		Stayers $s=2$	
	Chain Proportion $\hat{\pi}_s$	0.517 (0.046)		0.483 (0.046)	
		Class 1	Class 2	Class 1	Class 2
	Initial distribution $\hat{\delta}_{a\|s}$	0.342 (0.0430)	0.658 (0.0430)	0.081 (0.0200)	0.919 (0.0200)
		Latent transition probabilities $\hat{\tau}_{s,latent_{t+1}\|latent_t}$ t+1			
t *Latent variable at t*		Class 1	Class 2	Class 1	Class 2
1991 *a*	Class 1	0.765 (0.0610)	0.235 (0.0610)	1	0
	Class 2	0.168 (0.0430)	0.832 (0.0430)	0	1
1992 *b*	Class 1	0.714 (0.0580)	0.286 (0.0580)	1	0
	Class 2	0.13 (0.0380)	0.87 (0.0380)	0	1
1993 *c*	Class 1	0.747 (0.0520)	0.253 (0.0520)	1	0
	Class 2	0.126 (0.0420)	0.874 (0.0420)	0	1
1994 *d*	Class 1	0.756 (0.0570)	0.244 (0.0570)	1	0
	Class 2	0.097 (0.0330)	0.903 (0.0330)	0	1
1995 *e*	Class 1	0.757 (0.0540)	0.243 (0.0540)	1	0
	Class 2	0.108 (0.0350)	0.892 (0.0350)	0	1
1996 *f*	Class 1	0.869 (0.0570)	0.131 (0.0570)	1	0
	Class 2	0.089 (0.0350)	0.911 (0.0350)	0	1

1997	**Class 1**	0.786	0.214	1	0
g		(0.0560)	(0.0560)		
	Class 2	0.110	0.89	0	1
		(0.0330)	(0.0330)		
1998	**Class 1**	0.776	0.224	1	0
h		(0.0590)	(0.0590)		
	Class 2	0.065	0.935	0	1
		(0.0280)	(0.0280)		
1999	**Class 1**	0.790	0.21	1	0
i		(0.0610)	(0.0610)		
	Class 2	0.091	0.909	0	1
		(0.0270)	(0.0270)		
2000	**Class 1**	0.726	0.274	1	0
j		(0.0620)	(0.0620)		
	Class 2	0.082	0.918	0	1
		(0.0280)	(0.0280)		
2001	**Class 1**	0.777	0.223	1	0
k		(0.0780)	(0.0780)		
	Class 2	0.054	0.946	0	1
		(0.0290)	(0.0290)		
		Response probabilities $\hat{\rho}_{s,manifest|latent}$			
		Poor	**Non-poor**	**Poor**	**Non-poor**
	Class 1	0.755	0.245	0.885	0.115
		(0.0330)	(0.0330)	(0.0270)	(0.0270)
	Class 2	0.038	0.962	0.017	0.983
		(0.0140)	(0.0140)	(0.0040)	(0.0040)

Source: Derived from the BHPS 1991-2002
Standard errors in parentheses
N=519

Notation

$S=2$ is the number of chains in the mixed Markov Mover-Stayer model

$\hat{\pi}_s$ is the proportions of the sample in each of the s chains

$x_{91}, x_{92}, \ldots, x_{02}$ = observed poverty status (poor or not-poor)

$\hat{\delta}_{a|s}$ is the probability that a respondent belongs to one of A true latent classes at t=1 conditional upon membership in Markov chain s

$a=1,\ldots,A$, $b=1,\ldots,B$, ..., $l=1,\ldots,L$ are the twelve latent variables each with 2 classes corresponding to poverty/non-poverty at each of the twelve time points.

$\hat{\tau}_{s,latent_{t+1}|latent_t}$ are the transition probabilities between latent variables within each chain. Thus, $\hat{\tau}_{s,b|a}$, is the probability of belonging to class b $(b=1,2)$ at time point 2, given membership in class a at time point 1 and chain s. Stayers remain in their original class with a probability of 1.

$\hat{\rho}_{s,manifest|latent}$ are the conditional response probabilities and give the relationship between the observed variables and their latent counterparts for each chain. Deviations of the response matrix from identity give the degree of measurement error.

Table A5.9: Weighted transition probabilities: 50 % poverty line

	Short-term persistence: $Pr(poor_{t+1} \mid poor_t)$				Entry: $Pr(poor_{t+1} \mid not\text{-}poor_t)$			
	Observed Markov		Latent Mover-Stayer		Observed Markov		Latent Mover-Stayer	
t/t+1	Population	Children	Population	Children	Population	Children	Population	Children
91/92	0.407	0.449	0.914	0.833	0.059	0.066	0.023	0.046
92/93	0.409	0.337	0.912	0.818	0.054	0.075	0.019	0.052
93/94	0.495	0.507	0.942	0.876	0.047	0.067	0.013	0.044
94/95	0.513	0.548	0.950	0.884	0.050	0.077	0.016	0.057
95/96	0.527	0.647	0.945	0.926	0.043	0.072	0.010	0.054
96/97	0.597	0.694	0.961	0.936	0.055	0.079	0.020	0.064
97/98	0.551	0.556	0.948	0.920	0.045	0.078	0.014	0.062
98/99	0.589	0.564	0.969	0.943	0.055	0.079	0.016	0.040
99/00	0.553	0.526	0.959	0.913	0.050	0.070	0.012	0.033
00/01	0.450	0.380	0.920	0.797	0.040	0.048	0.013	0.021
01/02	0.578	0.479	0.972	0.860	0.045	0.055	0.010	0.042
Average	**0.515**	**0.517**	**0.945**	**0.882**	**0.049**	**0.070**	**0.015**	**0.047**

Table A5.10: Weighted transition probabilities: 60 % poverty line

	Short-term persistence: $Pr(poor_{t+1} \mid poor_t)$				Entry: $Pr(poor_{t+1} \mid not\text{-}poor_t)$			
	Observed Markov		Latent Mover-Stayer		Observed Markov		Latent Mover-Stayer	
t/t+1	Population	Children	Population	Children	Population	Children	Population	Children
91/92	0.574	0.651	0.879	0.879	0.078	0.118	0.052	0.087
92/93	0.555	0.523	0.870	0.852	0.077	0.103	0.045	0.067
93/94	0.588	0.597	0.884	0.869	0.074	0.106	0.033	0.065
94/95	0.597	0.556	0.915	0.874	0.070	0.088	0.041	0.050
95/96	0.629	0.596	0.909	0.874	0.068	0.095	0.028	0.056
96/97	0.673	0.663	0.946	0.932	0.075	0.090	0.034	0.046
97/98	0.651	0.586	0.911	0.889	0.070	0.078	0.038	0.057
98/99	0.654	0.615	0.922	0.884	0.070	0.071	0.034	0.034
99/00	0.673	0.627	0.948	0.891	0.070	0.079	0.027	0.047
00/01	0.628	0.540	0.866	0.858	0.061	0.071	0.025	0.042
01/02	0.637	0.581	0.946	0.885	0.071	0.079	0.025	0.028
Average	**0.624**	**0.594**	**0.909**	**0.881**	**0.071**	**0.089**	**0.035**	**0.053**

Table A5.11: Weighted transition probabilities: 70 % poverty line

	Short-term persistence: Pr($poor_{t+1}$ | $poor_t$)				Entry: Pr($poor_{t+1}$ | not-$poor_t$)			
	Observed Markov		Latent Mover-Stayer		Observed Markov		Latent Mover-Stayer	
t/t+1	Population	Children	Population	Children	Population	Children	Population	Children
91/92	0.643	0.733	0.852	0.901	0.108	0.163	0.076	0.116
92/93	0.716	0.779	0.936	0.927	0.094	0.153	0.052	0.112
93/94	0.639	0.660	0.865	0.872	0.090	0.134	0.036	0.104
94/95	0.687	0.727	0.936	0.919	0.094	0.138	0.046	0.063
95/96	0.725	0.743	0.943	0.938	0.093	0.123	0.038	0.053
96/97	0.733	0.744	0.924	0.928	0.096	0.150	0.039	0.060
97/98	0.722	0.754	0.924	0.966	0.083	0.119	0.037	0.072
98/99	0.734	0.749	0.952	0.923	0.089	0.132	0.038	0.038
99/00	0.707	0.667	0.910	0.849	0.093	0.122	0.046	0.047
00/01	0.679	0.658	0.888	0.826	0.090	0.132	0.039	0.033
01/02	0.709	0.693	0.946	0.919	0.084	0.093	0.034	0.041
Average	**0.699**	**0.719**	**0.916**	**0.906**	**0.092**	**0.133**	**0.044**	**0.067**

Source: Derived from the BHPS 1991-2002
Latent Mover-Stayer estimates are weighted by chain size.

Short-term persistent poor

$$Pr(Poor_{t+1} \mid Poor_t) = \left(\hat{\pi}_{s=mover} * \hat{\tau}^{mover}_{class1,t+1|class1,t}\right) + \left(\hat{\pi}_{s=stayer} * \hat{\tau}^{stayer}_{class1,t+1|class1,t}\right)$$

Poverty entry

$$Pr(Poor_{t+1} \mid Not\text{-}poort) = \left(\hat{\pi}_{s=mover} * \hat{\tau}^{mover}_{class1,t+1|class2,t}\right) + \left(\hat{\pi}_{s=stayer} * \hat{\tau}^{stayer}_{class1,t+1|class2,t}\right)$$

Chapter 6

Table A6.1: Coefficient estimates for the determinants of poverty, population, 60 % poverty line

Model	Static pooled probit		Dynamic pooled probit		Wooldridge RE	
Variable	UNBALANCED	BALANCED	UNBALANCED	BALANCED	UNBALANCED	BALANCED
Poverty at t=1			0.332***	0.352***	0.509***	0.547***
			(0.020)	(0.030)	(0.030)	(0.040)
Lag poverty status			1.195***	1.290***	0.613***	0.611***
			(0.020)	(0.030)	(0.020)	(0.030)
Sex of the head (ref=male)	0.024*	0.033	0.045***	0.062***	0.043***	0.054***
Female	(0.010)	(0.020)	(0.010)	(0.020)	(0.020)	(0.020)
Accommodation (ref=owned)						
Social rented	0.367***	0.397***	0.167***	0.234***	0.223***	0.294***
	(0.020)	(0.040)	(0.040)	(0.060)	(0.040)	(0.060)
Private rented	0.419***	0.338***	0.201***	0.233***	0.224***	0.236***
	(0.030)	(0.050)	(0.040)	(0.060)	(0.040)	(0.060)
Highest qualification of head (ref='A'-Levels or higher)						
O/CSE Level	0.328***	0.362***	0.076***	0.080***	0.077***	0.078***
	(0.020)	(0.030)	(0.020)	(0.030)	(0.020)	(0.030)
No qualifications	0.478***	0.540***	0.057**	0.111***	0.071***	0.122***
	(0.020)	(0.040)	(0.030)	(0.030)	(0.030)	(0.040)
Family type (ref=single with no children)						
Pensioner single	0.011	-0.007	-0.403***	-0.432***	-0.370***	-0.405***
	(0.040)	(0.070)	(0.070)	(0.100)	(0.070)	(0.100)
Pensioner couple	-0.148***	-0.096	-0.459***	-0.513***	-0.478***	-0.526***
	(0.040)	(0.070)	(0.060)	(0.080)	(0.070)	(0.090)
Couple with children	-0.080*	-0.021	0.014	-0.014	-0.017	-0.021
	(0.040)	(0.070)	(0.050)	(0.080)	(0.050)	(0.080)
Couple with no children	-0.168***	-0.120**	-0.223***	-0.217***	-0.244***	-0.226***
	(0.030)	(0.050)	(0.040)	(0.060)	(0.050)	(0.070)
Single with kids	0.418***	0.379***	0.406***	0.335***	0.393***	0.353***
	(0.050)	(0.080)	(0.060)	(0.090)	(0.060)	(0.090)
Age of head (ref= <=25)						
Age 26-34	-0.05	-0.146**	-0.025	-0.095**	-0.029	-0.141**
	(0.040)	(0.060)	(0.030)	(0.040)	(0.040)	(0.080)
Age 35-44	-0.156***	-0.275***	-0.034	-0.139***	-0.029	-0.195***
	(0.040)	(0.060)	(0.030)	(0.050)	(0.040)	(0.080)
Age 45+	-0.029	-0.146**	0.066**	0.013	0.074**	-0.019
	(0.040)	(0.060)	(0.030)	(0.050)	(0.040)	(0.080)
N. workers in household (ref=all adults in paid work)						
At least 1 paid worker but not all	0.058**	0.087**	0.099***	0.165***	0.101***	0.152***
	(0.030)	(0.040)	(0.030)	(0.040)	(0.030)	(0.040)
No paid workers	1.101***	1.097***	0.913***	0.897***	0.890***	0.863***
	(0.020)	(0.030)	(0.020)	(0.030)	(0.020)	(0.030)
N. children (ref= 1 child)						
0 children	-0.099**	-0.125*	-0.139***	-0.102	-0.115**	-0.089
	(0.040)	(0.070)	(0.050)	(0.080)	(0.050)	(0.080)
2 children	0.490***	0.526***	0.114**	0.203**	0.155***	0.245***
	(0.050)	(0.080)	(0.060)	(0.090)	(0.060)	(0.090)
3 children	0.771***	0.717***	0.226***	0.312***	0.281***	0.358***
	(0.050)	(0.080)	(0.070)	(0.100)	(0.070)	(0.100)
4+ children	1.242***	1.244***	0.573***	0.690***	0.631***	0.737***
	(0.060)	(0.090)	(0.080)	(0.120)	(0.090)	(0.130)
Disability status of head (ref=not disabled)						
Disabled	-0.266***	-0.234***	-0.055*	-0.081*	-0.067**	-0.088**
	(0.030)	(0.050)	(0.030)	(0.040)	(0.030)	(0.050)
Long term sick (N)	0.01	-0.022	0.036***	0.005	0.043***	0.017
	(0.010)	(0.020)	(0.010)	(0.020)	(0.010)	(0.020)
Number of observations (person-waves)	96,605	53,292	81,845	48,851	81,845	48,851
Log-likelihood	-34899.81	-18067.36	-29932.24	-13567.24	-28929.02	-12966.21
Model chi2	7728.51***	3278.78***	18600.03***	8242.52***	13990.87***	5421.31***
Rho (s.e.)					0.404 (0.009)	0.419 (0.032)
Test statistic for H0: Rho=0					2006.44***	1202.06***

Source: Derived from the BHPS (1991-2002). Notes: Standard errors in parentheses; * $p<0.10$ ** $p<0.05$ *** $p<0.01$

Table A6.2: Coefficient estimates for the determinants of poverty, children, 60 % poverty line

Model	Static pooled probit		Dynamic pooled probit		Wooldridge RE	
Variable	UNBALANCED	BALANCED	UNBALANCED	BALANCED	UNBALANCED	BALANCED
Poverty at t=1			0.297***	0.326***	0.435***	0.460***
			(0.040)	(0.080)	(0.040)	(0.100)
Lag poverty status			1.021***	1.089***	0.543***	0.639***
			(0.030)	(0.070)	(0.030)	(0.060)
Sex of the head (ref=male)						
Female	0.029	0.126***	0.063**	0.169***	0.062**	0.167***
	(0.020)	(0.050)	(0.030)	(0.050)	(0.030)	(0.060)
Accommodation (ref=owned)						
Social rented	0.539***	0.670***	0.249***	0.484***	0.317***	0.570***
	(0.040)	(0.090)	(0.070)	(0.140)	(0.080)	(0.160)
Private rented	0.262***	0.368***	-0.005	0.107	0.067	0.160
	(0.060)	(0.140)	(0.090)	(0.170)	(0.090)	(0.170)
Highest qualification of head (ref='A'-Levels or higher)						
O/CSE Level	0.339***	0.364***	0.146***	0.133*	0.137***	0.140**
	(0.030)	(0.060)	(0.040)	(0.070)	(0.040)	(0.080)
No qualifications	0.465***	0.512***	0.098*	0.12	0.091*	0.136
	(0.040)	(0.100)	(0.050)	(0.080)	(0.060)	(0.110)
Parental type (ref=couple)						
Single with children	0.497***	0.250***	0.524***	0.424***	0.543***	0.451***
	(0.040)	(0.090)	(0.060)	(0.120)	(0.060)	(0.120)
Age of head (ref= <=25)						
Age 26-34	0.132**	0.167	-0.053	0.045	-0.026	0.059
	(0.050)	(0.120)	(0.080)	(0.140)	(0.090)	(0.180)
Age 35-44	0.06	0.023	-0.063	0.14	-0.034	0.124
	(0.060)	(0.140)	(0.090)	(0.160)	(0.100)	(0.210)
Age 45+	0.142**	0.163	-0.082	0.411**	-0.041	0.420
	(0.060)	(0.170)	(0.100)	(0.200)	(0.110)	(0.250)
N. workers in household (ref=all adults in paid work)						
At least 1 paid worker but not all	0.099***	0.157*	0.109**	0.309***	0.101***	0.302***
	(0.040)	(0.080)	(0.050)	(0.090)	(0.050)	(0.080)
No paid workers	1.048***	1.187***	0.846***	0.878***	0.820***	0.878***
	(0.030)	(0.080)	(0.040)	(0.090)	(0.040)	(0.090)
N. siblings (ref= only child)						
1 sibling	0.349***	0.398***	0.218***	0.353***	0.227***	0.382***
	(0.040)	(0.100)	(0.050)	(0.120)	(0.060)	(0.120)
2 siblings	0.644***	0.554***	0.321***	0.482***	0.335***	0.502***
	(0.040)	(0.110)	(0.060)	(0.140)	(0.070)	(0.150)
3+ siblings	1.099***	0.942***	0.504***	0.784***	0.528***	0.793***
	(0.060)	(0.120)	(0.090)	(0.180)	(0.100)	(0.200)
Disability status of head (ref=not disabled)						
Disabled	-0.111	-0.274	0.144**	0.185	0.119*	0.167
	(0.070)	(0.200)	(0.070)	(0.140)	(0.080)	(0.160)
Long term sick (N)	0.087***	0.026	0.070***	0.058	0.076***	0.075*
	(0.020)	(0.040)	(0.020)	(0.040)	(0.020)	(0.050)
Number of observations (person-waves)	29,790	6,072	23,701	5,566	23,701	5,566
Log-likelihood	-11555.96	-2404.99	-7889.2793	-1859.2648	-7686.34	-1809.90
Model chi2	3770.08	699.8	5673.84	1491.12	4148.84	951.14
Rho (s.e.)					0.386 (0.017)	0.362 (0.032)
Test statistic for H0: Rho=0					405.88***	98.72***

Source: Derived from the BHPS (1991-2002)

Notes: Standard errors in parentheses; * p<0.10 **p<0.05 ***p<0.01

Table A6.3: Determinants of poverty (APEs): 50 % poverty line, population

Model	Static pooled probit		Dynamic pooled probit		Wooldridge RE	
Variable	**Unbalanced**	**Balanced**	**Unbalanced**	**Balanced**	**Unbalanced**	**Balanced**
Poverty at t=1			4.28***	3.54***	7.89***	6.39***
Lag poverty status			26.47***	27.70***	12.76***	11.94***
Sex of the head (ref=male)						
Female	0.63***	0.76***	1.00***	1.09***	1.06***	1.044**
Accommodation (ref=owned)						
Social rented	2.03***	2.57***	2.24***	2.95***	2.82***	3.74***
Private rented	5.90***	3.09***	3.50***	3.31***	4.18***	3.96***
Highest qualification of head (ref='A'-Levels or higher)						
O/CSE Level	4.00***	3.97***	1.29***	0.390	1.46***	0.38
No qualifications	6.18***	6.18***	0.380	0.230	0.58	0.33
Family type (ref=single with no children)						
Pensioner single	-1.84***	-2.18***	-4.18***	-4.15***	-4.43***	-4.11***
Pensioner couple	-5.34***	-4.06***	-6.36***	-6.36***	-7.37***	-6.89***
Couple with children	0.01	1.13	1.49*	1.41	1.64**	1.57
Couple with no children	-2.61***	-1.92***	-2.85***	-2.85***	-3.33***	-3.05***
Single with children	5.19***	5.74***	4.12***	4.96**	4.77***	5.49***
Age of head (ref= <=25)						
Age 26-34	-0.39	-2.19***	-0.83*	-1.65***	-0.76	-2.18***
Age 35-44	-1.45	-2.77	-1.05**	-2.36***	-1.13*	-3.02***
Age 45+	-0.04**	-1.59***	0.37	-0.56	0.75	-0.90
N. workers in household (ref=all adults in paid work)						
At least 1 paid worker but not all	2.29***	1.75***	1.11**	0.10	1.27***	0.10
No paid workers	19.66***	18.06***	13.49***	12.56***	13.60***	11.78***
N. children (ref= 1 child)						
0 children	-0.32	-0.63	-3.20***	-2.74***	-3.61***	-2.89***
2 children	5.7***	5.64***	-0.44	1.03	-0.29	1.32
3 children	11.80***	10.16***	1.41	2.00	2.12**	2.78**
4+ children	21.48***	20.35***	4.86***	6.60***	6.13***	7.59***
Disability status of head (ref=not disabled)						
Disabled	-4.33***	-3.45***	-1.36***	-0.95*	-1.68***	-1.14**
Long term sick (N)	-0.05	-0.56	0.02	-0.52**	0.14	-0.13**

Source: Derived from BHPS (1991-2002)
Notes: Standard errors in parentheses
* p<0.10 **p<0.05 ***p<0.01

Table A6.4: Determinants of poverty (APEs): 50 % poverty line, children

Model	Static pooled probit		Dynamic pooled probit		Wooldridge RE	
Variable	Unbalanced	Balanced	Unbalanced	Balanced	Unbalanced	Balanced
Poverty at t=1			4.61***	4.28**	7.65***	4.90***
Lag poverty status			23.5***	22.38***	10.74***	8.46***
Sex of the head (ref=male)						
Female	0.80**	3.82***	1.81***	3.88***	1.72***	3.18***
Accommodation (ref=owned)						
Social rented	5.44***	9.09***	6.25***	10.27***	7.16***	10.71***
Private rented	2.80**	3.44	1.24	4.22*	2.59**	5.39**
Qualification of head (ref='A'-Levels or higher)						
O/CSE Level	4.66***	5.54***	1.62***	2.09**	1.42**	1.55
No qualifications	6.21***	5.45**	0.27	-0.51	0.26	-0.13
Parental type (ref=couple)						
Single with children	5.44***	1.47	4.07***	4.50**	3.99***	3.84***
Age of head (ref= <=25)						
Age 26-34	4.16***	5.46**	0.31	-0.08	0.74	0.87
Age 35-44	2.71**	2.15	-0.25	-1.78	0.28	-0.77
Age 45+	4.94***	7.13**	0.07	0.94	0.53	1.64
N. workers (ref=all adults in paid work)						
At least 1 paid worker but not all	2.51***	3.20**	1.40*	0.41	1.43**	0.42
No paid workers	24.08***	25.88***	17.59***	15.36***	16.15***	12.31***
N. siblings (ref= only child)						
1 sibling	5.03***	7.06***	3.19***	7.15***	3.34***	6.54***
2 siblings	11.5***	11.27***	4.79***	10.85***	5.25***	10.11***
3+ siblings	21.83***	15.6***	8.49***	14.97***	9.13***	13.52***
Disability status of head (ref=not disabled)						
Disabled	-4.94***	-6.99***	-0.27	-1.57	-0.65	-1.45
Long term sick (N)	0.59**	-0.94	0.02	-0.56	0.01	-0.55

Source: Derived from BHPS (1991-2002)
Notes: Standard errors in parentheses
* p<0.10 **p<0.05 ***p<0.01

Table A6.5: Determinants of poverty (APEs): 60 % poverty line, population

Model	Static pooled probit		Dynamic pooled probit		Wooldridge RE	
Variable	Unbalanced	Balanced	Unbalanced	Balanced	Unbalanced	Balanced
Poverty at t=1			5.95***	6.05***	10.59***	11.17***
Lag poverty status			29.35***	31.6***	13.29***	12.86***
Sex of the head (ref=male)						
Female	0.48*	0.610	0.73***	0.94***	0.77***	0.92***
Accommodation (ref=owned)						
Social rented	8.12***	8.40***	2.80***	3.81***	4.22***	5.48***
Private rented	9.46***	7.11***	3.42***	3.81***	4.26***	4.36***
Highest qualification of head (ref='A'-Levels or higher)						
O/CSE Level	6.82***	7.12***	1.23***	1.23***	1.38***	1.35***
No qualifications	10.56***	11.46***	0.92**	1.72***	1.29***	2.14***
Family type (ref=single with no children)						
Pensioner single	0.230	-0.130	-5.69***	-5.67***	-5.87***	-5.98***
Pensioner couple	-2.84***	-1.750	-6.45***	-6.71***	-7.44***	-7.69***
Couple with children	-1.59*	-0.40	0.220	-0.21	-0.31	-0.35
Couple with no children	-3.25***	-2.18**	-3.41***	-3.14***	-4.11***	-3.63***
Single with children	9.57***	8.14***	7.45***	5.72***	7.94***	6.84***
Age of head (ref= <=25)						
Age 26-34	-0.99	-2.66**	-0.400	-1.42**	-0.52	-2.33**
Age 35-44	-3.05***	-4.89***	-0.540	-2.06***	-0.52	-3.18***
Age 45+	-0.580	-2.71**	1.05**	0.20	1.32**	-0.32
N. workers in household (ref=all adults in paid work)						
At least 1 paid worker but not all	1.17**	1.67**	1.62***	2.61***	1.84***	2.71***
No paid workers	26.91***	25.53***	18.13***	16.73***	18.82***	16.89***
N. children (ref= 1 child)						
0 children	-2.03**	-2.43*	-2.15***	-1.500	-1.99***	-1.47
2 children	10.70***	10.94***	1.87**	3.20**	2.84***	4.42***
3 children	18.82***	16.55***	3.87***	5.22***	5.44***	6.87***
4+ children	34.18***	33.50***	11.14***	13.4***	13.77***	16.42***
Disability status of head (ref=not disabled)						
Disabled	-4.87***	-4.01***	-0.87*	-1.20*	-1.18**	-1.46**
Long term sick (N)	0.21	-0.41	0.57***	0.080	1.66***	0.1

Source: Derived from BHPS (1991-2002)
Notes: Standard errors in parentheses
* p<0.10 **p<0.05 ***p<0.01

Table A6.6: Determinants of poverty (APEs): 60 % poverty line, children

Model	Static pooled probit		Dynamic pooled probit		Wooldridge RE	
Variable	**Unbalanced**	**Balanced**	**Unbalanced**	**Balanced**	**Unbalanced**	**Balanced**
Poverty at t=1			5.93***	6.58***	9.31***	9.07***
Lag poverty status			26.1***	28.28***	12.17***	13.61***
Sex of the head (ref=male)						
Female	0.62	2.76***	1.15**	3.08***	1.17**	2.85***
Accommodation (ref=owned)						
Social rented	13.42***	17.79***	4.87***	10.24***	6.56***	11.83***
Private rented	6.02***	8.97***	-0.09	2.01	1.28	2.91
Qualification of head (ref='A'-Levels or higher)						
O/CSE Level	7.46***	8.27***	2.69***	2.47*	2.61***	2.45**
No qualifications	11.22***	12.74***	1.83***	2.27***	1.77***	2.44***
Parental type (ref=couple)						
Single with children	12.25***	5.89***	11.05***	8.67***	11.80***	8.77***
Age of head (ref= <=25)						
Age 26-34	2.89**	3.77	-0.96	0.82	-0.49	1.03
Age 35-44	1.29	0.50	-1.16	2.54	-0.64	2.13
Age 45+	3.12**	3.69	-1.47	8.10**	-0.77	7.45
N. workers (ref=all adults in paid work)						
At least 1 paid worker but not all	2.16***	3.52*	2.02**	5.90*	1.95***	5.64***
No paid workers	30.68***	36.38***	20.35***	21.29***	20.21***	20.52***
N. siblings (ref= only child)						
1 sibling	7.45***	8.59***	3.96***	6.40****	4.31***	6.68***
2 siblings	15.42***	13.25***	6.20***	9.52***	6.80***	9.66***
3+ siblings	30.46***	26.14***	10.63***	17.78***	11.66***	17.91***
Disability status of head (ref=not disabled)						
Disabled	-2.30	-5.50	2.73**	3.57	2.32*	3.04
Long term sick (N)	1.86***	0.57***	1.28***	1.05***	0.26***	1.85*

Source: Derived from BHPS (1991-2002)
Notes: Standard errors in parentheses
* p<0.10 **p<0.05 ***p<0.01

Table A6.7: Determinants of poverty (APEs): 70 % poverty line, population

Model	Static pooled probit		Dynamic pooled probit		Wooldridge RE	
Variable	**Unbalanced**	**Balanced**	**Unbalanced**	**Balanced**	**Unbalanced**	**Balanced**
Poverty at t=1			6.12***	4.93***	12.62***	11.02***
Lag poverty status			36.19***	38.70***	17.34***	16.88***
Sex of the head (ref=male)						
Female	0.250	0.250	0.46*	0.150	0.47	0.14
Accommodation (ref=owned)						
Social rented	14.71***	14.95***	4.67***	4.47***	6.58***	6.45***
Private rented	13.11***	10.83***	5.73***	5.49***	6.81***	6.16***
Highest qualification of head (ref='A'-Levels or higher)						
O/CSE Level	8.78***	9.49***	0.90**	0.95**	1.16***	1.22***
No qualifications	14.81***	15.80***	0.87*	2.29***	1.27**	2.78***
Family type (ref=single with no children)						
Pensioner single	4.13***	2.170	-4.36***	-4.46***	-3.72***	-3.97***
Pensioner couple	-1.360	-1.780	-5.48***	-6.08***	-6.27***	-6.85***
Couple with children	-2.03**	-1.01	-0.380	0.53	-1.08	0.05
Couple with no children	-4.37***	-3.52***	-4.52***	-4.60***	-5.68***	-5.59***
Single with children	12.89***	10.68***	8.32***	7.93***	9.28***	8.72***
Age of head (ref= <=25)						
Age 26-34	-1.66*	-3.20**	-0.220	-0.920	-0.27	-1.61
Age 35-44	-4.07***	-6.17***	0.260	-1.210	0.73	-1.94
Age 45+	-0.690	-2.060	2.41***	1.64*	3.53***	2.04
N. workers in household (ref=all adults in paid work)						
At least 1 paid worker but not all	4.99***	4.78***	5.32***	5.63***	5.91***	6.05***
No paid workers	30.90***	30.03***	19.56***	18.55***	21.33***	20.01***
N. children (ref= 1 child)						
0 children	-3.99***	-4.55***	-1.93**	-2.010	-1.59*	-1.48
2 children	14.13***	15.33***	3.67***	3.52**	5.56***	5.80***
3 children	21.68***	22.06***	5.48***	6.39***	8.08***	9.69***
4+ children	40.66***	43.34***	19.22***	18.95***	23.81***	25.87***
Disability status of head (ref=not disabled)						
Disabled	-5.50***	-4.17***	-2.09***	-1.90***	-2.37***	-2.15***
Long term sick (N)	0.44*	-0.21	0.93***	0.63**	1.98***	0.30***

Source: Derived from BHPS (1991-2002)
Notes: Standard errors in parentheses
* p<0.10 **p<0.05 ***p<0.01

Table A6.8: Determinants of poverty (APEs): 70 % poverty line, children

Model	Static pooled probit		Dynamic pooled probit		Wooldridge RE	
Variable	**Unbalanced**	**Balanced**	**Unbalanced**	**Balanced**	**Unbalanced**	**Balanced**
Poverty at t=1			6.66***	5.80***	12.81***	10.95***
Lag poverty status			32.25***	35.04***	14.29***	13.58***
Sex of the head (ref=male)						
Female	-0.06	1.10	0.28	1.97**	0.18	1.73*
Accommodation (ref=owned)						
Social rented	19.58***	21.76***	6.97***	9.41***	9.53***	12.17***
Private rented	8.38***	11.99***	3.10*	3.83	4.34***	3.60
Qualification of head (ref='A'-Levels or higher)						
O/CSE Level	9.52***	12.32***	1.44**	2.75*	1.65**	2.94**
No qualifications	13.74***	16.38***	0.94	1.27	0.78	1.25
Parental type (ref=couple)						
Single with children	16.51***	10.68***	13.57***	9.88***	15.01***	10.42***
Age of head (ref= <=25)						
Age 26-34	-0.08	-3.92	-4.68***	-5.38	-4.26***	-4.49
Age 35-44	-2.59*	-7.34*	-5.77***	-5.10	-4.80***	-4.11
Age 45+	-1.34	-4.79	-6.00***	-3.30	-5.22***	-2.19
N. workers (ref=all adults in paid work)						
At least 1 paid worker but not all	6.25***	6.99***	6.14***	8.79***	6.21***	8.98***
No paid workers	32.67***	36.33***	20.30***	19.85***	20.69***	20.76***
N. siblings (ref= only child)						
1 sibling	9.39***	11.36***	4.73***	7.06***	5.68***	8.62***
2 siblings	17.93***	16.75***	8.30***	10.25***	10.04***	12.67***
3+ siblings	37.31***	39.62***	18.03***	29.14***	21.46***	33.95***
Disability status of head (ref=not disabled)						
Disabled	-5.50***	-8.03	-2.09	-2.15	-1.91	-1.52
Long term sick (N)	2.58***	1.08	1.76***	2.01***	0.40***	4.01**

Source: Derived from BHPS (1991-2002)
Notes: Standard errors in parentheses
* p<0.10 **p<0.05 ***p<0.01

Table A6.9: Share of raw state dependence attributable to genuine state dependence and individual heterogeneity

		Population			**Children**		
	Sample	**50%**	**60%**	**70%**	**50%**	**60%**	**70%**
(i) ASD	Unbalanced	0.54	0.55	0.65	0.47	0.55	0.59
	Balanced	0.47	0.55	0.61	0.45	0.51	0.59
(ii) GSD	Unbalanced	0.13	0.13	0.17	0.11	0.12	0.14
	Balanced	0.12	0.13	0.17	0.08	0.14	0.14
(iii) Share of ASD due to GSD	Unbalanced	0.23	0.24	0.27	0.23	0.22	0.24
	Balanced	0.25	0.23	0.28	0.19	0.27	0.23
(iv) Share of ASD due to observed heterogeneity	Unbalanced	0.51	0.46	0.44	0.50	0.53	0.46
	Balanced	0.41	0.43	0.37	0.50	0.45	0.41
(v) Share of ASD due to unobserved heterogeneity	Unbalanced	0.25	0.29	0.29	0.27	0.25	0.30
	Balanced	0.34	0.34	0.36	0.31	0.29	0.36
(vi) Share of ASD due to total heterogeneity	Unbalanced	0.77	0.76	0.73	0.77	0.78	0.76
	Balanced	0.75	0.77	0.72	0.81	0.73	0.77

Source: Derived from the BHPS, 1991-2002.

Calculation of quantities

i. Aggregate state dependence (ASD)

$$\text{ASD}=\left(\frac{\sum_{i\in\{P_{it-1}=1\}}\Pr(P_{it}=1\mid P_{it-1}=1)}{\sum_i P_{it-1}}\right)-\left(\frac{\sum_{i\in\{P_{it-1}=0\}}\Pr(P_{it}=1\mid P_{it-1}=0)}{\sum_i (1-P_{it-1})}\right)$$

ii. Genuine state dependence (GSD) derived from the average partial effect of the lag poverty status regressor from the dynamic random effects (DRE) model.

iii. Fraction of aggregate state dependence (ASD) attributable to genuine state dependence (GSD):

$$\frac{GSD_{DRE}}{ASD}$$

iv. Fraction of ASD attributable to observed heterogeneity is calculated as:

$$1-\frac{GSD_{DPP}}{ASD}$$

where DPP refers to the dynamic pooled probit model which controls for state dependence and observed heterogeneity only.

v. Fraction of ASD attributable to unobserved heterogeneity:

$$\left(1-\frac{GSD_{DRE}}{ASD}\right)-\left(1-\frac{GSD_{DPP}}{ASD}\right)$$

vi. Fraction of ASD attributable to total (observed and unobserved) heterogeneity

$$1-\frac{GSD_{DRE}}{ASD}$$

Chapter 7

Table A7.1: LCGA model fit statistics: population, 60 % of median income poverty line

Classes	LL	N parameters	BIC	Entropy	LMR LRT	LMR LRT p-value k-1
1	-58443.78	3	116917.01			
2	-45939.46	7	91947.61	0.753	24387.32	0.0000
3	-44625.03	11	89358.00	0.661	2563.55	0.0000
4	-43854.98	15	87857.14	0.664	1501.84	0.0000
5	-43644.83	19	87476.10	0.681	409.85	0.0381
6	-43531.52	23	87288.73	0.66	220.99	0.0070
7	-43374.72	27	87014.37	0.686	277.67	0.0000
8	-43300.44	31	86905.07	0.648	269.95	0.0674

Source: Derived from the BHPS 1991-2002 unbalanced panel.

Table A7.2: Classification table: population, 4-class model

		Average posterior probability			
		Class 1	**Class 2**	**Class 3**	**Class 4**
Most likely group	**Class 1**	**0.735**	0.095	0.053	0.117
	Class 2	0.089	**0.727**	0.090	0.093
	Class 3	0.059	0.058	**0.874**	0.008
	Class 4	0.131	0.092	0.014	**0.763**

Source: Derived from the BHPS 1991-2002 unbalanced panel.

Table A7.3: Classification table for the 5-class model, population

		Average posterior probability				
		Class 1	**Class 2**	**Class 3**	**Class 4**	**Class 5**
Most likely group	**Class 1**	**0.873**	0.026	0.056	0.008	0.037
	Class 2	0.064	**0.682**	0.086	0.066	0.102
	Class 3	0.107	0.041	**0.771**	0.017	0.061
	Class 4	0.022	0.050	0.123	**0.730**	0.076
	Class 5	0.069	0.081	0.048	0.054	**0.748**

Source: Derived from the BHPS 1991-2002 unbalanced panel.

Table A7.4: Estimated parameters for the four-class model, population

Trajectory k	**Intercept** η_{Ik}	**Linear Slope** η_{Sk}	**Quadratic Slope** η_{Qk}
OP	-0.584 (0.152)***	-0.097 (0.053)*	-0.021 (0.006)***
IP	-3.315 (0.219)***	0.385 (0.070)***	-0.011 (0.005)**
NP	-4.01 (0.130)***	-0.382 (0.037)***	0.034 (0.003)***
PP	0.00 (N.A.)	0.323 (0.036)***	-0.030 (0.003)***

Source: Derived from the BHPS 1991-2002 unbalanced panel.

Coefficients are in logit scale.
* p<0.10 **p<0.05 ***p<0.01

Table A7.5: Profile of trajectory group membership, population

	PP	OP	IP	NP	Group size
All individuals	**10.49**	**11.15**	**9.76**	**68.59**	**100**
Sex of head					
Male	8.27	10.15	9.17	72.41	45.37
Female	12.41	12.02	10.28	65.29	54.63
Tenure					
Owned	**6.04**	**7.63**	9.08	77.25	69.46
Social rented	**21.98**	**22.44**	**12.81**	**42.77**	22.19
Private rented	**13.72**	10.32	8.24	67.72	8.35
Education level of head					
A-Levels or above	**6.43**	**6.64**	7.26	79.67	35.08
O/CSE Level	9.57	12.22	10.74	67.48	34.84
No qualifications	**18.64**	**17.39**	**12.70**	51.27	30.08
Family type					
Pensioner single	**24.34**	**19.45**	**13.25**	**42.95**	8.10
Pensioner couple	**16.26**	12.50	12.59	58.65	7.92
Couple with children	8.24	12.02	10.98	68.76	41.79
Couple with no children	**3.38**	**5.27**	8.45	82.90	20.56
Single with children	**30.18**	**23.78**	10.49	**35.55**	7.06
Single with no children	10.44	8.38	**6.28**	74.90	14.57
Age of head					
<25	**18.01**	10.61	9.15	62.23	4.95
25-34	9.87	11.42	8.66	70.05	23.90
35-44	**6.66**	10.30	8.37	74.66	26.59
45+	11.11	11.69	11.75	65.46	44.56
Household emplyment status					
All adults in work	**3.53**	**7.56**	8.38	80.54	56.19
At least one adult in paid work but not all	**5.54**	8.69	11.42	74.35	14.13
Household without paid work	**26.07**	**19.16**	11.40	**43.37**	29.68
Number of children					
0	9.84	8.53	8.70	72.94	48.57
1	**6.33**	10.31	11.62	71.73	15.72
2	9.86	13.27	8.82	68.05	22.91
3	**14.71**	**18.60**	12.07	54.62	9.32
4+	**34.78**	**20.99**	**15.22**	**29.01**	3.48
Disability status of head					
Non-disabled	10.46	11.03	9.66	68.86	96.90
Disabled	11.48	**15.19**	**13.07**	60.25	3.10
N. Long-term sick in household					
0	9.66	11.15	9.83	69.36	94.49
1	12.95	13.11	10.95	62.99	4.42
>4	**32.91**	**6.12**	**4.43**	56.54	1.09

Source: Source: Derived from the BHPS 1991-2002 unbalanced panel.
Notes: Characteristics at t=1.
Lightly shaded boxes indicate substantially lower-than-average probabilities (at least 30 lower than average).
Darkly shaded boxes indicate substantially higher-than-average probabilities (at least 30 per cent higher than average).
OP=Moving out of poverty; IP=Moving into poverty; NP=never poor; PP=permanently poor
N=11616

Table A7.6: Predicted probabilities of trajectory group membership, population

Profile	OP	IP	PP	NP
1) Advantaged	0.06	0.06	0.03	0.85
2) Sex of head: Male → female	0.06	0.06	0.03	0.85
3) Tenure: Privately owned → social rented	0.14	0.08	0.05	0.73
4) Qualification of head: A-Levels or above → no qualifications	0.13	0.10	0.07	0.70
5) Parental status of head: Couple → lone	0.11	0.07	0.07	0.75
6) Age of head: 26-34 → <=25	0.07	0.08	0.04	0.81
7) Household employment status: All employed→ workless	0.17	0.09	0.17	0.57
8) Number of children: 2 → 4+	0.13	0.16	0.13	0.58
9) Non-disabled head → disabled head	0.06	0.06	0.02	0.86
10) N. LT sick: 0 → 2	0.05	0.06	0.04	0.85
11) Disadvantaged (accumulation of 2-10)	0.14	0.06	0.79	0.02

Source: Source: Derived from the BHPS 1991-2002 unbalanced panel.
OP=Moving out of poverty; IP=Moving into poverty; NP=never poor; PP=permanently poor

Appendix B: Glossary of Terms

Average partial effects

The impact of a change in an explanatory variable on the risk of experiencing poverty, averaged over the population distribution of observed and unobserved heterogeneity.

Balanced panel

Panel data set in which each individual is observed in every panel wave, thus, there is no missing data on individuals.

Cardinal comparison of poverty

Comparison based on numerical estimates of poverty indices.

Dynamics of poverty

The heterogeneous patterns of poverty across different time dimensions, namely, point-in-time, short-term transitions, and long-term trajectories. It is used interchangeably with the term 'poverty dynamics'.

Headcount ratio

Measures the proportion of people in the population with incomes below a given poverty line. It is also known at the poverty rate.

Latent variables

Variables that are not directly observed (for example, longitudinal patterns of poverty) but are inferred from manifest variables, which are directly measured or observed (for example, annual poverty status).

Observed heterogeneity

Differences in the risk of poverty that arise from observed characteristics, for example, family size, employment status, gender.

Ordinal comparison of poverty

Comparisons that rank poverty across income distributions, without quantifying the precise numerical differences that exist between these distributions. Thus, ordinal comparisons stated whether poverty in one income distribution is higher or lower than poverty in another distribution.

Percentiles

Equal sized groupings that result from ranking in ascending order all household or individual incomes in a population into one hundred groups, each comprising 1 per cent of the population. The tenth percentile, denoted *P10*, is the income level that divides the bottom ten per cent from the rest, and the median or the fiftieth percentile is denoted *P50*.

Percentile ratios

Ratios of selected percentiles, which are used to quantify the relative distance between two points of the income distribution. For example, the *P90/P10* compares the wealthiest and poorest 10 per cent of the population.

Poverty gap index

Percentage average shortfall of income of the poor relative to the poverty line. It gives a measure of 'depth' of poverty as it considers the distance of incomes from the poverty line.

Poverty transitions

Changes in poverty status between two consecutive time points. These can be classified as:

i. Short-term poverty persistence: being poor in two consecutive waves.
ii. Poverty entry: being poor in one year conditional upon being non-poor in the previous year.
iii. Poverty exit: being non-poor in one year conditional upon being poor in the previous year.
iv. Non poor: being non-poor in two consecutive waves.

Prevalence of poverty

The percentage of individuals who are poor at least once over the period of the study.

Quantiles

Equal sized groupings that result from ranking in ascending order all households or individuals in a population based on a particular characteristic (income in this thesis). For example, division into five equal groups, each comprising 20 per cent of the population, gives quintiles.

Squared poverty gap index

Squares the average shortfall between an individual's income and the poverty line, thus attributes more weight to larger shortfalls. It gives a measure of the 'severity' of poverty as greater weight is placed on shortfalls of income furthest from the poverty line.

True state dependence

The experience of poverty itself (in contrast to observed or unobserved individual heterogeneity) increases the risk of poverty in the future.

Unbalanced panel

Panel data set in which not every individual is observed in every panel wave, thus, there is missing data on individuals.

Unobserved heterogeneity

Differences in the risk of poverty that arise from unobserved characteristics such as ability, preferences, motivation.