Pasi Moisio

Poverty dynamics according to direct, indirect and subjective measures

Modelling Markovian processes in a discrete time and space with error

The research presented in this series has been approved for publication after undergoing a formal referee evaluation process.

ISBN 951-33-1403-0 (online publication)
ISBN 951-33-1587-8 (printed publication
ISSN 1236-0732

STAKES
National Research and Development Centre for Welfare and Health

RESEARCH REPORT 145

Acknowledgements

I wish to thank all the people who have helped me during my work on this doctoral thesis whilst I was working at the Department of Political and Social Sciences, at the European University Institute in Florence.

I want to express my deepest gratitude to Richard Breen from Nuffield College, Oxford, who has been a supportive and excellent supervisor. He guided my doctoral studies skilfully and tirelessly, and with a genuine interest in my work. I also want to thank the other three members of the Examining Board, Jaap Dronkers from the European University Institute, Markus Jäntti from the Åbo Akademi, Turku, and Chris Whelan from the ESRI, Dublin, for helpful comments and clarifying discussions during the examination. Also, I thank Nicky Owtram and Ellie Smith for correcting the English in my thesis.

This thesis would not have been possible without the financial support of the Academy of Finland, which I recognise with gratitude. I am also very grateful to the people at the Institute for Social and Economic Research (ISER) at the University of Essex for their support during my two periods there as an ECASS researcher. I also wish to thank the National Research and Development Centre for Welfare and Health (STAKES) for being supportive and flexible when I needed time to finish my doctoral thesis.

The biggest gratitude I owe to my wife Hanna, who has shared the frustration as well as the joy during the many years of work that went into this thesis.

Abstract

Pasi Moisio. Poverty dynamics according to direct, indirect and subjective measures. Modelling Markovian processes in a discrete time and space with error. National Research and Development Centre for Welfare and Health (STAKES). Research Report 145. ISBN 951-33-1587-8

A debate is going on about how transitory poverty really is in affluent welfare states. Research findings indicate that usually poverty spells are of a relatively short duration. On the other hand, studies have also shown that poverty is very persistent among a specific part of the population. This study tries to find an explanation for these two seemingly contradictory findings. Modelling panel data from ten EU countries with measurement models, this study is able to reveal that the classical Mover-Stayer model can explain the dynamics of poverty and that, if measurement error is ignored, the mobility in poverty and deprivation transition tables is over-estimated. The mover group and the measurement error explain why there are two seemingly conflicting pictures of poverty dynamics.

The financial poverty, housing deprivation and subjective deprivation indicators from the European Community Household Panel (ECHP) were used in four repeated measurements. The descriptive analysis revealed that the population is heterogeneous when relating to poverty dynamics and that the dynamics are similar across the countries and across the direct, indirect and subjective indicators. With the time-heterogeneous partially Latent Mover-Stayer model, we were able to identify these groups: the first group are stayers in poverty, the second are stayers not in poverty and the third group are the movers. With different poverty classifications in different countries, we have different fractions of population classified into these three groups, but the groups of stayers and movers are identified in every transition table. The preliminary finding on common poverty dynamics were confirmed with the Latent Constant Fluidity model, which was fitted into the layered transition tables. The three poverty measures in the ten countries have very similar poverty transition probabilities, especially when random error is corrected to, as the error operates at different levels between countries and indicators.

Three main conclusions can be drawn from the results. First, there is high poverty mobility but poverty spells seem to concentrate to the same group of people. Second, poverty mobility is over-estimated by 25 to 50 per cent if the random error is ignored. Third, poverty dynamics, both the absolute mobility as well as transition probabilities, seem to have a striking affinity across countries and indicators, despite the large differences in the cross-sectional poverty and deprivation rates. We studied only three classifications in ten EU countries, but we can expect that other poverty and deprivation classifications would lead us similar conclusions about poverty dynamics if turned into longitudinal measures.

Keywords: multidimensional poverty, poverty dynamics, measurement error, latent class models

Abstract in Finnish

Pasi Moisio. Poverty dynamics according to direct, indirect and subjective measures. Modelling Markovian processes in a discrete time and space with error. Stakes, Tutkimuksia 145. Helsinki 2004. ISBN 951-33-1587-8

Tutkittaessa köyhyysliikkuvuutta hyvinvointivaltioissa törmätään ristiriitaiseen kuvaan köyhyydestä. Köyhyysjaksot ovat yleensä sangen lyhyitä, mutta samaan aikaan köyhyys on hyvin sitkeää osassa väestöä. Tämä tutkimus hakee selitystä tälle ristiriitaiselle tulokselle. Selitys löytyi, kun tutkimuksessa onnistuttiin mallintamaan kymmenen EU maan paneeliaineisto niin kutsutulla Mover-Stayer -mallilla, joka sallii mittausvirheen. Mallin identifioima toistuvaisköyhien ryhmä (movers) sekä mittausvirheen aiheuttama liikkuvuuden yliestimointi selittävät miksi köyhyys näyttää olevan toisaalta ohimenevä, toisaalta sitkeä ilmiö.

Köyhyyttä mitattiin kolmella eri indikaattorilla: suhteellisella tulometodilla, asumisen puutteisiin liittyvällä deprivaatiomittarilla sekä subjektiivisella käsityksellä kotitalouden taloudellisesta tilanteesta. Aineistona oli neljä aaltoa European Community Household Panel (ECHP) kotitaloustiedustelusta. Jo deskriptiivinen analyysi paljasti, että väestö on heterogeeninen köyhyysliikkuvuuden suhteen ja että liikkuvuuden muoto on samanlaista käytetyillä suoralla, epäsuoralla ja subjektiivisella köyhyysmittarilla. Latentti Mover-Stayer -malli vahvisti alustavista tuloksista ensimmäisen, kun malli identifioi kolme selkeää ryhmää väestössä: ei koskaan köyhyyttä kokevat, toistuvaisköyhät ja pitkäaikaisköyhät. Näiden kolmen ryhmän suhteelliset koot vaihtelevat maittain, samoin kuin eri köyhyysmittareita käytettäessä. Mutta kyseiset kolme ryhmää ovat identifioitavissa jokaisessa maassa ja kaikilla kolmella mittarilla. Toinen alustava tulos sai vahvistuksen, kun köyhyysliikkuvuustaulujen siirtymätodennäköisyydet onnistuttiin mallintamaan Latentin Constant Fluidity -mallin avulla. Köyhyysliikkuvuuden muoto on hyvin samanlainen suoraa, epäsuoraa tai subjektiivista mittaria käytettäessä, varsinkin sen jälkeen kun satunnaisen mittausvirheen vaikutus on korjattu, sillä mittausvirheen suuruus vaihtelee maiden ja mittareiden välillä.

Tutkimuksen tuloksista voidaan vetää kolme johtopäätöstä. Ensinnäkin, liikkuvuus köyhyysrajan ympärillä on korkea, mutta lyhyet köyhyysjaksot näyttävät kasaantuvan samaan toistuvaisköyhien ryhmään. Toiseksi, köyhyysliikkuvuus yliestimoidaan 25–50 prosenttia mikäli mittausvirheen vaikutusta paneelissa ei kontrolloida. Kolmanneksi, köyhyysliikkuvuus on yllättävän samanlaista (sekä volyymiltaan että siirtymätodennäköisyyksien osalta) eri maiden välillä ja eri mittareilla. Tämä siitä huolimatta, että köyhyysasteissa on suuria maittaisia eroja, samoin kuin eri mittaustavat tuottavat hyvin eri köyhyysasteet. Tutkimuksessa analysoitiin köyhyysliikkuvuutta kolmella eri köyhyysmittarilla, mutta on todennäköistä, että myös muut köyhyys- ja deprivaatiomittarit antavat samansuuntaisia tuloksia mikäli niitä käytetään pitkittäisissä tutkimuksissa.

Avainsanat: moniulotteinen köyhyys, köyhyysliikkuvuus, mittausvirhe, latent class -mallit

Abstract in Swedish

Pasi Moisio. Poverty dynamics according to direct, indirect and subjective measures. Modelling Markovian processes in a discrete time and space with error. Stakes, Undersökningar 145. Helsingfors 2004. ISBN 951-33-1587-8

Då man studerar fattigdomens dynamik i välfärdsstater stöter man på en paradoxal fattigdomsbild. Fattigdomsperioderna är i allmänhet mycket korta, men samtidigt är fattigdomen påfallande seg hos en del av befolkningen. Den här undersökningen försökte hitta en förklaring till detta motsägelsefulla resultat. Förklaringen hittades i och med att panelmaterial från tio EU-länder kunde modelleras med den så kallade Mover-Stayer-modellen, som tillåter mätningsfel. Modellen identifierade en grupp (movers) som drabbas av återkommande fattigdom. I kombination med den övervärdering av dynamiken som orsakas av mätningsfel förklarar denna grupp varför fattigdomen tycks vara dels ett tillfälligt, dels ett beständigt fenomen.

Fattigdomen mättes med tre olika indikatorer: relativ inkomst, en deprivationsmätare som mäter bristerna i boendet samt den subjektiva uppfattningen om hushållets ekonomiska situation. I undersökningen användes material från EU:s hushållsenkät, European Community Household Panel (ECHP), i fyra upprepade mätningar. Redan den deskriptiva analysen visade att befolkningen är heterogen vad gäller fattigdomsdynamiken och att dynamiken är likadan med alla mätare, dvs. den direkta, den indirekta och den subjektiva fattigdomen. Den latenta Mover-Stayder-modellen bekräftade det första preliminära resultatet i och med att den identifierade tre klara grupper bland befolkningen: de som aldrig upplevt fattigdom, de som i återkommande perioder upplever fattigdom och de som är permanent fattiga. Dessa gruppers relativa storlekar varierar dels mellan olika länder, dels beroende på fattigdomsmätare. De tre grupperna kan emellertid identifieras i alla länder och med alla tre mätare. Det andra preliminära resultatet bekräftades i och med att övergångssannolikheterna i tabellerna över fattigdomsdynamik kunde modelleras med hjälp av Latent Constant Fluidity-modellen. Fattigdomsdynamiken visade sig följa samma mönster oavsett om man mäter med den direkta, den indirekta eller den subjektiva mätaren. Särskilt tydlig var likformigheten då effekten av godtyckliga mätningsfel hade korrigerats, eftersom mätningsfelets storlek varierar mellan olika länder och olika mätare.

Tre konklusioner kan dras av undersökningens resultat. För det första är mobiliteten stark på bägge sidor om fattigdomsgränsen, men de korta fattigdomsperioderna tycks koncentreras till samma grupp som i återkommande perioder drabbas av fattigdom. För det andra övervärderas fattigdomsdynamiken med 25–50 procent ifall effekten av mätningsfelet i panelen inte kontrolleras. För det tredje är fattigdomsdynamiken beträffande såväl volym som övergångssannolikhet överraskande likadan i olika länder och mätt med olika mätare. Detta trots att skillnaderna i fattigdomsgrad är stora mellan olika länder och trots att olika mätmetoder ger mycket varierande fattigdomsgrader. Undersökningen analyserade fattigdomsdynamiken med tre fattigdomsmätare, men det är sannolikt att också andra fattigdoms- och deprivationsmätare ger liknande resultat om de används i longitudinella studier.

Nyckelord: Mångdimensionell fattigdom, fattigdomsdynamik, mätningsfel, latent class modeller

Contents

List of figures and tables

Figures

List of tables

Introduction

What is understood by 'poverty' has changed in western industrialised countries. One obvious reason for this is that the standards of living have risen. Poverty is no longer seen merely as malnourishment and a lack of shelter, as was the case 50 years ago. Living conditions have risen rapidly in the last half of the century and there is now a welfare state established in every EU country, in one form or another. However, not only what is seen as the minimum standard of living, but also expectations of what is required in a modern society have risen. To be able to have the minimum expected way of living in an affluent welfare state requires more, and new, kinds of capabilities and resources than were needed in the pre-modern society.

But not just expectations and requirements of the normal way of living have changed, also the experience of poverty has changed. In the early decades of industrialised societies poverty was the normal and expected condition for large parts of the population. The majority of the working class, for example, shared in the experience of poverty. In a post-industrialised society, poverty has become an increasingly individualised experience and less a simple reflection of the social class structure. Post-industrialised societies have become more fluid and unpredictable, at least for the individual. Though the social class of the family that a person is born into still determines very much the future of the person, post-industrialised societies are 'open' in a sense that both upward and downward mobility are common. A post-industrialised society is not as rigid as was an industrial society and many argue that post-industrialised societies become even more unpredictable when they are maturating. In a matured post-industrial society poverty becomes more and more detached from social structures like social classes. In other words, poverty is believed to become individualised, as is the entire post-industrialised society. Individualised poverty means that poverty becomes, or has already become, more related to (wrong) individual decisions, to life course events and to the personal biography of an individual than to the social class structure. The landscape of poverty is not anymore simply a reflection of the social class structure as it was in a industrial society. Poverty is now seen to be a private and non-material total social exclusion from society (e.g. Silver 1994; Strobel 1996).

It is a strong statement to say that a social structure like social stratification does not have an effect on the distribution of poverty anymore or that poverty is totally transient in the mature post-industrial society. These kinds of statements are often presented in the contemporary poverty research under the label 'individualisation thesis'. The individualisation thesis argues that poverty has become a mainly transitory experience in relatively few people's lives and that poverty is nowadays more connected to individual choices and life-course events than to the social structures of stratification (Leisering & Leibfried 1999, 9). The extent of poverty's transience can be observed by studying its dynamics. Poverty dynamics, like every dynamic process, have two aspects: absolute and relative. Absolute mobility refers to the ratio between the numbers of movers versus stables. Relative mobility, or fluidity, refers to the relative transition probabilities, for example, to the transition probabilities into and out from poverty. (Erikson & Goldthorpe 1992, 55–9.) We can compare countries according to their absolute poverty mobility, but the relative poverty mobility can tell us something about the social structures in those countries. For example, is there a social structure that causes predetermined poverty for some or does everyone equally risk experiencing poverty? In other words, is the population divided into permanently different poverty trajectories and how different are these trajectories?

Studying the dynamics of poverty requires panel data. Repeated measurements bring some additional problems to measurement since the random measurement errors do not nullify each other's effect in panel data as they do in cross-sectional data. If we understand measurement according to the classical test theory, i.e. that an observed value is the 'sum' of the true value and measurement error, we can expect that the estimates of poverty dynamics will be over-estimated if random error in the panel data is ignored. This danger has been recognised in recent longitudinal poverty studies (e.g. Duncan 1997). Random measurement errors can be tackled in panel data by using measurement models that relate observed measures to a latent structure with probabilistic relationships, which allow each manifest measurement to have a separate measurement error. As we will see, these two main themes, the measurement error and the heterogeneity of the population, penetrate this study.

The book is structured into seven chapters. The first chapter starts with an introduction to poverty research. A short, general definition of poverty is given, following a review on established explanations as to why there continually seems to be a fraction of the population worse off than others, even in the most affluent societies. Then, in section two, some moral and social justifications are presented for why poverty should be tackled. Section three is a presentation of the development of poverty measurement, from the early 20th century to this day. It shows that after the late 1970s, poverty measurement has developed and expanded rapidly. Preceding the conclusion, the link between social policy and poverty measurement is reviewed in the section four. It is shown that different methods to measure poverty carry different social policy implications.

The second chapter gives a more detailed introduction to poverty measurement. In section two different definitions of poverty are presented and their similarities are highlighted. Also it is shown how the concept of deprivation is an inseparable part of the concept of poverty. In section three, the operationalisation of the concept of poverty is presented. The head-count classification is selected as the type of indicator that will be used in the analyses. In the fourth section the head-count classification is expanded to multidimensional and longitudinal measurement. The former is presented as a method where (indirect) income poverty indicators and (direct) objective and subjective deprivation indicators are used side-by-side, the latter as a method where the same indicator is used in repeated measurements. The fifth section is committed to the presentation of the scale of measurement and to the issues of reliability and validity in the measurement of poverty. The chapter ends with a section presenting the conclusions and selections made in the second chapter.

The third chapter presents the research questions, the data and the methods that are used for modelling poverty dynamics. The chapter starts with an introduction section, after which the research hypotheses are presented in section two. There are four research hypotheses which this study tries to answer or, better, falsify. The first hypothesis is derived from the individualisation thesis, stating that the population is heterogeneous when relating to the dynamics of poverty. The second research hypothesis, derived from the classical test theory, states that random error causes mobility to be over-estimated in poverty and deprivation transition tables. The third hypothesis states that relative poverty mobility, i.e. fluidity, is common between different poverty indicators. This hypothesis is derived from the theory that different poverty indicators measure the same process but in its different phases. The fourth hypothesis states that relative poverty mobility is common also across the ten countries selected for study. The hypothesis is derived from recent studies suggesting that the transition of poverty has a common pattern between countries.

After the research hypotheses have been addressed, the ECHP panel data and the three poverty classifications that are used for analyses will be presented. The three dichotomous poverty classifications are financial poverty, housing deprivation and the subjective deprivation measures. They are assumed to measure different dimensions of poverty indirectly, directly and subjectively. Four waves of the ECHP from ten countries are used to construct a four-way transition table for each poverty classification. The descriptive poverty figures for these three poverty classifications are presented in section four. Log-linear modelling is presented as the method for building measurement models that can be used for testing the research hypothesises. For this, the fifth section presents the basics of log-linear modelling and its latent variable extension, latent class modelling, and how these techniques can be used for building Simple, Mixed and Latent Markov chain models. The chapter ends with a summary section.

In the fourth chapter we try to answer the first and second research hypotheses. A family of Markov chain models is used to model the poverty dynamics and to find out if the population is heterogeneous and also how much mobility is over-estimated due to measurement error. The transition tables of the three poverty classifications are studied separately: the dynamics of financial poverty are studied in section two, the dynamics of housing deprivation in section three and the dynamics of subjective deprivation in section four. The true change is separated from the error using the parameter estimates of a partially latent Mover-Stayer model. The first empirical chapter ends with a summary of the findings of the analyses.

The third research hypothesis is dealt with in the fifth chapter. The transition tables of financial poverty, housing deprivation and subjective deprivation are combined into one layered transition table and modelled again with log-linear modelling techniques. The aim is to test whether relative poverty mobility in the transition tables is common to all three. This testing is done with the Latent Constant Fluidity model that allows for error in the model. This way we can compare the true poverty dynamics in the three transition tables, without noise. The measurement model also enables us to compare the reliability of the three poverty measures, which is covered in the third section. In the fourth section all the empirical findings made in the second empirical chapter are compiled and summarised.

Chapter six is the final empirical chapter and it is devoted to the fourth research hypothesis. For this, the transition tables from the ten countries are combined into three layered transition tables and modelled with the same Latent Constant Fluidity model. In section two, the likelihood ratios of the model are studied separately for each country, so that we can see if some countries have a 'deviant' structure of poverty dynamics. In the third section, the true and observed transition probabilities are compared. The aim is to study whether the error is operating in different levels in different countries, causing additional variance between countries in their poverty dynamics. The fourth section summarises the results from the country comparisons.

The seventh and final chapter summarises and ties up the empirical findings made in the study and interprets them in a larger context of theories and policy implications. The second section of the concluding chapter is devoted to linking the research findings of the study to previous studies on poverty and poverty dynamics, and trying to interpret the results in the larger theoretical context of social stratification. It will recommend that longitudinal poverty studies recognise that the over-estimation in panel data should be taken seriously, otherwise there is a substantial risk for biased mobility estimates. The third section presents some policy recommendations derived from this study. Some new and some old policy recommendations are given for changing the view of poverty from static to dynamic.

1 Poverty and social policy

1.1 Introduction

This chapter gives a short introduction into sociological poverty research. After the introductory section, we approach the issue of poverty by pondering three questions that need to be answered, implicitly or explicitly, in every poverty study. These questions are; what is poverty, why is there poverty and why study it?

In section two, we show that poverty is an object of normative, administrative and methodological interest for various actors. This means that it is inevitably a political concept and therefore, *per se*, a continuously debated concept (Alcock 1993, 3). There is one exception; the so-called relative definition of poverty (Townsend 1979, 31) is largely accepted in present-day poverty research in welfare states. However, this fragile unanimity quickly falls short when an attempt is made to measure relative poverty. After answering the question of what poverty is, a general explanation is given as to why there seems to be poverty, even in the most affluent societies. The distribution of resources and the desirable style of living determine the conditions and the expectations of living without deprivation. For this both theories about the distribution of resources and writings about increased living standards are reviewed. The second section ends with the third question; why should we study poverty? It is argued that poverty should be studied so that we can attempt to resolve the problem, because poverty causes negative moral and social consequences.

In section three, the historical development of poverty measurement is presented. Since the beginning of modern poverty measurement in the early 20th century, sociological poverty research has developed into several different schools. The use of multiple indicators and longitudinal panel data are presented as the state-of-the-art approaches in contemporary empirical poverty research.

In section four the close connection between the measurement of poverty and social policy is reviewed. We show that each method of poverty measurement carries implicitly a social policy implication on how poverty could, and should, be reduced. The chapter ends with a summary in the fifth, and final, section.

1.2 Why Poverty?

Three questions arise when poverty is brought into discussion. These questions are: what is poverty, why is there poverty and what is its significance? The first question is a matter of theoretical conceptualisation, a task that has not reached an unambiguous outcome in the public debate or in the field of poverty research. It is also difficult to give a satisfactory answer to the question of why there is poverty. One of the pioneers of poverty research, Seebohm Rowntree, put it bluntly, over a hundred years ago, by saying that to be able to give a satisfactory answer to the question, one has to give an answer to the whole 'social question', i.e. to all social problems. However, without opening the Pandora's box of social theory about the link between micro actors and social structures, we can present some general theories on why there always seems to be a fraction of population who are worse-off, even in the most affluent societies. Maybe the easiest question out of the three is why poverty should be studied. Poverty is studied so that we can do something about it.

1.2.1 What is poverty?

In general terms poverty can be defined as living below some threshold of the distribution of welfare. This means that poverty is closely related to, though not the same as, inequality. If a society is equal but the standard of living is low across the society, it follows that everyone in the society is poor, not that there is no poverty. The reason why special attention is paid to the bottom of the welfare distribution is the belief that there is a level of welfare below which people suffer some form(s) of deprivation (see Creedy 1998, 25). This is why the concept of a poverty threshold (or poverty line, cut-off point, etc.) has a central place in definitions of poverty and in poverty research in general. The poverty threshold represents the fundamental poverty measurement idea that there is a threshold below which attaining a customary way of living in the society is no longer possible. In other words, a relative difference in welfare (or in resources or amenities) can produce a qualitative difference in functioning within a society.

An awkward situation occurs in poverty research in that, to be able to do empirical poverty research, one is forced to select one definition out of several alternative definitions. Luckily, most of the established definitions of poverty are similar, once one goes beyond the discursive surface of them. Most empirical poverty studies can be grouped either by the definition of Peter Townsend or Amartya Sen. Although they used different terms and formulated resources, needs and capabilities and their connections in different ways, their definitions hold many similarities.

Although Sen and Townsend severely debated between themselves whose definition is correct (e.g. Townsend 1985; Sen 1985), both Sen and Townsend define poverty (put very simply) as incapability to achieve an acceptable way of living in the society in which they live, because of lack of resources and amenities.

Townsend (1979, 31) is generally seen as giving the most popular and lasting definition of relative poverty in sociological poverty studies. According to him, poverty can be defined objectively and applied consistently only together with the concept of relative deprivation. Townsend defined poverty as the lack of resources to participate in activities, and have the living conditions and amenities that are customary in the society to which one belongs. In other words, he defined relative poverty as life-style deprivation caused by the lack of resources. Thus, the concepts of poverty and deprivation are inseparable and often treated without distinction. Townsend's definition on poverty as relative deprivation corresponds to the definition of poverty as a lack of capability, refined by Sen (2000, 4). Both relative and capability definitions of poverty emphasise the lack of income and financial resources as (one of) the main sources of poverty and deprivation, but poverty is seen as a wider and more complex phenomenon than just the lack of income. There have been numerous attempts to give a more precise and a valid definition of poverty, but these similar definitions by Townsend and Sen have maintained their central position. However in this study, we lean towards Townsend's definition.

How much and what kind of amenities and resources are needed to avoid deprivation is relative. It depends on the society in hand, the ability to make use of the resources and the needs that have to be met. For example, a Londoner needs more money to buy a monthly tube ticket than a farmer in the Kenyan countryside earns in a month. If a Londoner does not have money to buy the monthly tube ticket and is therefore incapable of getting to work every morning, we can say that he is poor because he cannot function in his society and achieve the expected way of living (at least by his employer). The fact that the income that the Londoner has would probably make him a rich man in Kenya, does not change the fact that in London he is poor. So the lack of amenities or resources is relative, but the outcome of this inadequacy, i.e. incapability to function in the society or achieve an acceptable way of living, is absolute.

However, empirical poverty research has failed, despite intensive search in the past decades, to find an indisputable threshold in the distribution of resources after which basic functioning in the society becomes difficult. The most likely explanation for this is that the resources materialise into welfare very differently among individuals, depending on numerous individual, social and societal factors, as pointed out by Ringen (1985). As a result, all methods to measure poverty are open to criticism.

1.2.2 Why is there poverty?

If it is difficult to give a simple answer to the question what *is* poverty, it is even more difficult to give a satisfactory answer to the question, *why* there is poverty. At a general level we can say that the extent and level of poverty in a society at a given historical moment can be explained, on the one hand, by the supported style of living and living conditions, and on the other, the production and allocation of resources (see Townsend 1979, 917). The distribution of resources and desirable style of living are in constant interaction and together they determine the conditions and expectations of what it is to be living without deprivation.

The expectations of a decent life have risen in (post-)industrialised countries during the 20th century together with improved living conditions. The standard of living of the poor in a contemporary welfare state is probably higher than the standard of living of an average person a hundred years ago. The welfare state has erased famine and fatal epidemics among the poor, which are still fact of everyday life among the poor in some developing countries. Some argue that there is no longer real poverty in welfare states, only people who feel ashamed of their inability to reach the commonly desired style of living. The modest diet and even the long waiting period for public hospitals that the poor in welfare states have to face would be luxuries for the poor in a developing country. Some argue that social shame is not the same as poverty.

However, even the earliest poverty researchers admitted that avoiding famine is not enough in a modern society. To be able to earn a living in a modern society one has to have, for example, access to a newspaper and have decent clothes for a possible job interview. Hence, although the argument that one is not *really* poor if basic needs are met has a certain face validity, it quickly falls short once one starts to ponder what the minimum resources and amenities are that are needed for functioning in a modern society. For example, in future societies employers will probably put job advertisements solely on the internet, because it is cheaper and because the internet has become so common. One could say that access to the internet would then be a necessity in that society, not a luxury. Hence, the common expectations of a normal life increase what is actually needed to function in the society. In other words, what is needed to avoid poverty.

So the expectations of a decent life govern the minimum standard of living that should be achieved. The allocation of resources governs who do not have resources to achieve this minimum. There is a wide range of literature on the production and distribution of resources and about the institutions that have risen to control them. An explanation as to why the allocation of wealth seems to be very skewed has been sought from both the different abilities of individuals as well as from the institutions of society. Most of the explanations fall somewhere between the opposite polls of pure individualistic and pure institutional explanations.

The orthodox economic theory, which sees the distribution of resources as the outcome of the rational maximization of producers and consumers and the equilibrium of their interaction, can be viewed as one of the most individualistic explanations for the skewed income distribution, while sociological theories explain the distribution of resources from the institutions and the macrostructure of society. So-called underclass and life cycle theories, as well as functionalism, refer both to individual characteristics and institutional factors when explaining the skewed allocation of resources and wealth.

The orthodox economic theory explains the shape of personal income distribution from the distribution of intelligence and other abilities. Since mental and physiological abilities are more or less normally distributed in a population, it might be assumed that the distribution of personal income also resemble a normal distribution. Empirical studies, however, do not confirm the hypothesis that personal income distribution would be normal. It has been proposed that the distribution is lognormal, because different abilities are not additive in nature but multiplicative. In other words, a combination of skills and abilities is more rewarded in the markets than what a simple sum of these skills and abilities would be. Also the inheritance of wealth is assumed to skew the distribution by giving advantages to some for example in the form of easier access to education. However, the orthodox theory serves as a point of reference in the contemporary economic research on income inequality.

Numerous other theories have been proposed in economics to explain income inequality. For example, so-called multiplicative theories, which are based on the idea that wealth is a product of numerous and simultaneous variables (Roy 1951). We know that wealth and power tend to accumulate generation after generation to the same families, distorting the distribution of resources. Even if the distribution of abilities among individuals is assumed to be normal, families with wealth and power can ensure their offspring have better chances of success by using their wealth and social capital. More theories on (income) inequality in economics have been developed around the ideas of human capital and dual labour markets. For a more extensive review of theories of (income) inequality in economics, see Sahota (1978), Townsend (1979, 77–9) and Atkinson & Bourguignon (2000).

The functionalist explanation of inequality is based on the assumption that some occupations are functionally more important for the society as whole than other occupations (Davis & Moore 1945; Townsend 1979, 83–5). Since some occupations are more important for a society to function, there have to be rewards assuring that these more important occupations are filled by motivated and talented individuals. Functionalism views society as a holistic system where the most able people should carry out the most important tasks. Inequality is the unavoidable device that guarantees that the most able persons seek the most demanding and rewarding occupations. The other side of this functional selection mechanism is that a part of the society is necessarily worse-off. Hence, it is not difficult to see how the functionalistic view of society easily highlights the personal characteristics of the poor when explaining poverty. However, the functional explanation of poverty, and functionalism in general, in the social sciences has lost a lot of the importance that it once had (for the decline of the functionalistic paradigm in the social sciences, see Gouldner, 1970). Perhaps the most crucial weakness of functionalism is that it ignores the obvious fact that people with wealth and prestige can influence to the distribution and magnitude of rewards in society by protecting or augmenting their own privileges (see Wrong 1959).

Sociological theories explain the allocation of resources using the structure of social stratification that is based on the allocation of positions in the production system. These positions can be classified into social classes that are also divided, in some respect, according to their life-styles and values. The social class structure is considered to be a crucial social phenomenon that illustrates both the attachment of individuals to social macro structures as well as the distinctions and differentiations experienced in everyday life. It is also often assumed that there exists a special bond or a sense of solidarity between persons in the same social class. There are two main traditions which conceptualise social class in sociology. The (neo-)marxist tradition emphasises the importance of the conflict of class interests as the major source of class formation (e.g. Wright 1997). The (neo-)weberian tradition emphasises the differences in life chances and market positions (Breen 2002).

There are three main labour-market-related criteria that are used to classify people into social classes: according to their (i) general position in the labour markets, their more (ii) precise position in the production unit and (iii) the nature of their employment relation (Erikson & Goldthorpe 1992, 35–47). Although these three criteria come from the Weberian tradition, in general the same criteria are used in the marxist tradition (Sørensen 2000). Using these three criteria, the three main social classes can be distinguished: (1) employers who buy the labour of others, (2) self-employed workers without employees, who neither buy nor sell labour, and (3) employees who sell their labour and therefore place themselves under authority and control. Several intermediate classes are proposed into this rough trichotomy to fine-tune the picture. For example, employees are often divided into those who sell manual labour and those who sell their mental output. Traditionally poverty is seen as a problem mainly afflicting the working classes, i.e. those who are selling the most easily expendable labour, manual labour.

Underclass theories can be seen to have their origin in the social class theories. As the name indicates, underclass theories concentrate on the segment of population that, in a way, is below social classes, a modern *Lumpenproletariat* so to speak. Maybe the best-known presentation of a underclass theory is given by Oscar Lewis (1966). According to him, the poor create a subculture of poverty for themselves that is transferred from the one generation to the next. This subculture includes counterproductive social values, attitudes and behaviour that reinforce exclusion and segregation from 'normal' society. This way the poverty culture creates a permanent underclass living in intergenerational poverty. (For later developments of the theory, see Marks 1991.)

A spin-off of the underclass debate has been the so-called welfare-dependence research, where the research interest has been whether the welfare state is one of the institutions causing the culture of poverty (e.g. Bane & Ellwood 1994). Welfare dependence research has concentrated mainly on the United States, since European poverty and welfare research has been reluctant to adopt underclass theories and no doubt welfare-dependence studies have been one reason for this. Instead in European welfare studies, theories under the concepts of the new poor and social exclusion have been more popular when poverty (or the new poverty) is explained. The concept of social exclusion in particular leans more towards Durkheim and his theories about the disruption of social fabric than to the social class theories. (See e.g. Silver 1994; Room 1995.)

The life cycle (or minority group) theory was originally presented by Rowntree (1941). His discovery in the late 18th century city of York was that poverty was usually only avoided in a common man's life when he was in his prime working age, without children. Hence, when observed through an entire life-span, poverty seems to have a cyclical nature. Social policy transfers, namely old-age pensions and child-benefits, have eroded this vicious cycle by subsidising families with children and the elderly who are outside the labour markets (Kangas & Palme 2000). The life cycle approach has developed into a rich research tradition that studies how life events trigger, or help to exit, poverty. These changes are either related to the life cycle, like parenthood and old age, or to other life-event changes like unemployment or divorce. (E.g. Bradbury et al. 2001.)

Theorists of post- or late modernity have argued that the importance of social class as a main source of individual identification and orientation has weakened as the 'great narratives' of modernity lose their power (e.g. Beck et al. 1994). The primary institutions, like the social class structure, religion and family, are replaced by 'secondary' institutions like mass media, the labour market and the welfare state as the main source of personal identification and determinants of life courses. This is a direct critique against the sociological explanations of poverty presented earlier. Sociological explanations are based on the idea of social stratification, which is now claimed to have lost its importance in people's life. Individuals are more and more free to choose their style of living, values and life goals. Life in a 'post-modern' society, something that is seen to follow the modern society, is seen as a series of personal choices and it is this self-created biography that should be studied, if one wants to understand poverty in the post-modern society.

This individualisation thesis, as it has often been called, has pointed out several aspects to poverty that the traditional sociological poverty research has neglected. A modest application of the individualisation thesis has produced the so-called life course approach in welfare studies that emphasise the social risk management throughout an individual's life-span (e.g. Leisering & Leibfried 1999, 29–33). But a strong and rigid interpretation out of the individualisation thesis, i.e. that social structures do not have, or have only mild, influence on people's life, is difficult to find empirical support for. Empirical studies have shown that structural factors play a significant role when explaining poverty and that people's freedom of life choices is very much limited by several factors, even in the most developed and richest countries in the world (Andreb & Schulte 1998; Layte & Whelan 2002).

1.2.3 Why should we study poverty?

Maybe the easiest question out of the three is why we should study poverty. Poverty is studied so that we can do something about it (see Gordon & Townsend 2000, 142–6). Poverty research can be seen as one major brand of welfare research, which studies the level and distribution of welfare in the society (see Ringen 1985, 102). The welfare of citizens, or a lack of it, is studied because we believe that we can influence the level and the distribution of welfare in the society by public policy. Public services and social transfers are directed in such a way that they are believed to give the best result. What is then seen as the 'best result' depends on the social policy model of the country and its presumption of what is understood by 'deprivation' or 'poverty' and the reasons causing them.

Social programs against poverty can be justified by referring either, or both, to the equality of outcome and to the equality of opportunity. The latter is especially difficult to override, since the equality of opportunity can be justified both by moral arguments as well as by referring to the efficiency of production and the aggregate good. The equality of opportunities is one of the leading normative goals in the western (post-)industrialised countries. There are many arguments about the role and content of equality of outcome, but there is broad consensus that opportunities should be equal (see Lipset & Bendix 1959, 2–3).

Perhaps child poverty research can be seen as the topic in poverty research in which equality of opportunity is most explicitly brought up (see e.g. Bradbury et al. 2001). A child cannot be held responsible for the conditions that he or she is born into, but these conditions can have a huge influence on the opportunities that he or she will have in his or her life. So poverty is not just a question of inequality of conditions i.e. that some families are worse-off, but poverty is also a question of intergenerational inequality, inequality of opportunities. A poor family may pass to its children poorer opportunities in life. For example, education is assumed to be financed completely or partly by parents. There are means for students from less well-off families to finance their education, for example stipends or state guaranteed low-interest student loans. However, children from better-off families can compete for student places and concentrate on their studies without worrying about financing their studies and allocating part of their time and energy while studying to paid work.

As this book is emphasising the importance of changing the view of poverty from a static to a dynamic one, we should also look at policy programs that aim to alleviate poverty over a longer time-scale. Social transfers and public services do not only lessen poverty and inequality now, but they also prevent poverty and inequality being passed from one generation to the next.

1.3 Development of poverty measurement

If there is a fragile unanimity on the definition of poverty, there is a good deal of disagreement among sociologists over how poverty should be *measured* (e.g. Nolan & Whelan 1996, 10–14). Three rivalling schools or approaches in poverty research have been distinguished: absolute poverty, relative poverty and relative deprivation approaches (Ringen 1985). These three approaches can be seen also as stages in the historical development of poverty measurement. However, all the three approaches still have their own supporters and the three approaches co-exist in current empirical poverty research. We can also include a fourth and fifth approach in the series, the multidimensional and longitudinal approaches, which have filtered into European sociological poverty research during the 1990s. These five poverty measurement approaches or schools can be briefly described as follows.

The modern measurement of poverty can be seen as starting in Rowntree's pioneering work in the city of York at the beginning of the 20th century, which laid the first conceptual and theoretical foundation for the measurement of poverty. His definition of poverty as minimum subsistence, and the food-basket method for measuring it, dominated the measurement of poverty for almost a century. This approach, where poverty is conceptualised as the minimum physiological capability to function, can be called as the *absolute poverty approach.* (Ringen 1985.) In the absolute approach poverty is understood as living under the minimum below which physical efficiency could be maintained. Bare subsistence rather than the way of living draws the line between the poor and the non-poor.

A very influential US Census poverty threshold, which provides a time-series from 1959 onwards, is often referred to as an absolute threshold. Since 1969 the dollar amount poverty threshold has only been adjusted with the consumer price index. This dollar amount threshold, or better the matrix of dollar amount threshold for different size and type of households, was originally estimated from the prize of a minimum food basket, multiplied by three, since empirical studies in the 1950s indicated that an average family uses one third of its incomes on food. The US census poverty threshold has been heavily criticised for not taking into account the rise in the general standards of living, using incomes before taxes as the indicator of resources, neglecting non-cash benefits, using the same dollar amount threshold throughout the United States and so on. The US Census has made only minor revisions to the original measure, but since the end of the 1990s it has published figures based on an experimental poverty measure. The experimental measure uses incomes after taxes and takes into account non-cash subsidies. (US Census Bureau 2004.) Most likely due to the monolithic status of the US census poverty threshold, the debate on poverty and poverty measurement in the United States has been more policy oriented, concentrating on this official threshold (see Citro & Michael 1995, 17–9; Fisher 1992).

In Europe, on the contrary, during the 1970s there was a crucial change in the understanding of poverty in academic, as well as in the public, debate. Poverty began to be conceptualised increasingly in relative terms: as resources or living standards that fall too far below an average, or acceptable, level of income/welfare. At the same time as this shift from absolute to relative poverty, the causes of poverty were laid out for focused study. Before this, the causes of poverty were rarely studied and only indirectly referred to in the choice of definitions and measurement methods. (Townsend, 1971; 1979). Peter Townsend was the leading name in this new *relative poverty approach.* Although the definition of poverty changed from absolute to relative and the poverty threshold from a biological necessity to a function of income, the measurement of poverty itself remained the same – it was measured as a lack of material resources.

This change to understanding poverty as relative can also be linked to a larger paradigm shift in the social sciences, namely the ending of functionalism, which, based on theories of Talcott Parsons and others, did not necessarily regard it a problem when one person's income is lower than another's. Inequality, if it was vested on the value of each individual contribution to societal welfare, was, in the eyes of the functionalists, functional and valuable for society and was even required for its survival (see e.g. Gouldner, 1970).

However, there is a logical break between the definition of poverty and indicators that were used for measuring poverty, both in the absolute and relative approaches, as Ringen (1985) pointed out in his influential article. Poverty is measured as a lack of material resources, but the definition of poverty refers to the standard of living. This contradiction gave rise to a criticism in the 1980's, especially after several empirical studies showed that the link between low material resources and a low standards of living was much more complex than a simple causal one: it was shown that equal material resources do not necessarily result in equal welfare and that welfare is not necessarily a function of material resources. Ringen (1985) argued that a lack of material resources is neither a necessary nor a sufficient condition for poverty. He endorsed the relative definition of poverty, but at the same time criticised the idea that material resources were taken as the sole indicator of welfare. This is why he insisted that poverty should be observed and measured directly as poor living conditions i.e. deprivation, not indirectly as the lack of resources. This led to a third school in poverty research: *the relative deprivation approach*.[1]

Sen (1979) on the other hand, criticised both the relative poverty and the deprivation approaches because according to him, poverty and deprivation are not just relative, they also reflect visible hardships that can, and should, be objectively observed in absolute terms. He made a distinction between resources and the capability to function, pointing out that relative deprivation in the former can yield absolute deprivation in the latter. Sen's point was that one surely needs relatively more resources in a rich industrial country to be able to function, for example, to be able to be seen in public without shame. But this functioning, i.e. appearing in public without shame, is absolute. His formulation on the connections between resources, capabilities and functioning is much more sophisticated than the simplistic summary presented here. For a more extensive review on the Sen's capability approach, see Sen (1983), Sen (1985) and Sen (1992).

By the end of the 1980s there was also an ongoing debate on how 'inadequate living conditions' should be measured and on who should define who is poor: academic researcher's 'objectivity' was put against common people's 'sense' using consensus methods and individual subjective opinions (Mack & Lansley 1985; Piachaud 1987). It was also suggested that resources within the household are not necessarily allocated according to the needs of members of the household (Jenkins 1991). In short, the methodology and theoretical bases of poverty and welfare studies expanded during the 1970s and 1980s. From time to time, there were controversies between these three 'schools' of thought on how poverty research should be conducted and how poverty and deprivation should be defined and, subsequently, measured (e.g. Townsend 1985; Sen 1985; Ringen 1988; Donnison 1988).

After intensive research during the 1970s and 1980s, it became clear that all the ways to distinguish between the poor and the non-poor are hampered by the practicalities of actually measuring things like low resources or poor living conditions. The most disturbing consequence of these problems is that quite different groups are identified as poor by different methods and poverty indicators. As a solution, some researchers proposed during the 1990s that we should treat different methods and indicators as alternative ways to gain information on the same complex social problem (e.g. Muffels et al. 1992; Kangas & Ritakallio 1998;

[1] It was in fact Ringen (1985) who originally presented these three stages in the measurement of poverty.

Moisio 2004). Hence, different methods give somewhat different pictures of poverty (in society) and some researchers came to the conclusion that none of these pictures are indisputably 'better' than the other. This why they suggested that poverty should be measured with a set of several indicators, containing direct, indirect and subjective measures, which would give complementary information on the different aspects of poverty. This *multidimensional approach* quickly gained popularity, especially in administrative reports and studies (e.g. Eurostat 1988).

In the early 1990s there also emerged criticism towards how poverty is understood in European welfare studies, not just how it was measured. The critics said that the concept of poverty is unable to embrace the dynamic nature of hardships, and the temporal and spatial accumulation of social disadvantages. Poverty research at that time was also criticised because it was still seen as merely describing the problem of poverty, leaving the social processes that create poverty and deprivation in a society aside. The concept of social exclusion was considered to be more appropriate to grasp the dynamic nature of social disadvantages and, further, shed light on the processes that are behind poverty and deprivation. The theories of social exclusion can be seen as a response to the American underclass theories that have a long and rich tradition in the US poverty research (see Coser 1965; Wilson 1987). However, the theories of social exclusion usually make a clear separation from the underclass theories. (e.g. Silver 1994; Room 1995.) However, after a decade of intensive research, many academics have abandoned the idea that the concept of social exclusion could replace the concepts of poverty and deprivation. The main reason for this being that there is uncertainty as to how much analytical value the concept of social exclusion has in the empirical research, mainly due its lack of conceptual and theoretical clearness (see Sen 2000, 1–2).

Berghman (1995) pointed out that these allegedly new, dynamic aspects that the concept of social exclusion brought into welfare research were already an integral, but hidden, part of the concepts of poverty and deprivation. He also presented a conceptual framework to relate the ideas of social exclusion, impoverishment, poverty and deprivation in a dynamic way. According to him, the concepts of poverty and deprivation deal with static outcomes whereas, impoverishment and social exclusion refer to a process. Deprivation is different from poverty in that deprivation is multidimensional, whereas a lack of material resources i.e. poverty, is one-dimensional. Social exclusion, on the other hand, is a concept that refers to a multidimensional process, where impoverishment is only one of its dimensions.

It might have been that the concept and theories of social exclusion smoothed the way for the *dynamic approach* from the US to Europe. By the end of the 1990s, more and more European researchers drew attention to the fact that poverty had generally been measured in Europe as a static condition. There was a demand for longitudinal analyses and datasets on poverty (e.g. Bradbury et. al 2001; Layte &

Whelan 2003). It became acknowledged that analysing poverty as a longitudinal phenomenon was essential both to understand it and for the development of social policy. However, it is most likely that the static view on poverty would have changed in Europe to a dynamic one, even without the debate around social exclusion. In the United States, the longitudinal approach in the measurement of poverty has already been undertaken in the 1980s and the research has produced a rich and wide range of literature on poverty dynamics (Bane & Ellwood 1986; Hill 1981; Duncan 1984).

In contemporary European poverty research, we know a lot about cross-sectional poverty; how poverty is distributed in the population, what parts of the population are in a high poverty-risk etc. There is a much smaller body of knowledge about the dynamics of poverty; how persistent, or transitory, poverty states are, how families move in and out from poverty across the family formation cycle, how poverty transmits itself over the generations etc. To meet this deficit, Eurostat and member states launched the European Community Household Panel (ECHP) in the mid-1990s and the panel has instigated longitudinal poverty research in Europe (see Atkinson et al. 2002). Longitudinal and comparative analyses on poverty in Europe have been executed, for example, Duncan et al. (1993), Krause (1998), Layte & Whelan (2003), Fouarge & Muffels (2000). However, there is still much that is unknown about the dynamics of poverty in Europe, so European longitudinal poverty studies will produce new information about the dynamics of poverty for many years.

1.4 Measurement of poverty and social policy

The measurement of poverty always serves some purpose - identifying and calculating the poor is not a purpose on its own. Most often poverty measurement serves the needs of social policy. Since the emergence of a welfare state, social transfers and services redistribute and consume a large part of gross domestic production. Already, the size of the welfare state means that there is a need for information about whom it targets and evaluations of how well the welfare state responds to the social issues and problems that are deemed its responsibility. Information from poverty measurements is used to plan, target and modify social policy to make it more effective in, for example, alleviating poverty. Often other branches of public policy, like employment, housing and fiscal policies, are used together with social policy in this task, if not even understood as parts of general social policy.

There is no clear and widely accepted definition of social policy. The concept is simply most often taken as given and is rarely explicitly defined. A favoured and lasting definition for social policy is that of T.H. Marshall (1975, 15), who interpreted it as the use of political power to supplement and modify operations of the economy in order to achieve outcomes that the economy would not achieve on its own. This correction of the economic system is guided by other values than those determined by market forces. The narrow interpretation of the social policy definition could view these corrections as redistribution of welfare, done by direct or indirect social transfers and public or subsidised services. This narrow interpretation generally prevails in welfare studies, where poverty research is usually also included. This means that when referring to social policy in this book, it is done within this narrow meaning defined above.

There are three alternative comprehensions or models on what is social policy and what is its purpose. These models can be named as the residual welfare model, the adjunct welfare model and the redistributive welfare model of social policy. These three models crystallise different moral and ideological views about the means and ends of social policy by putting a different weighting between the state, private market and family providing welfare and hedging against social risks (Titmuss 1974, 30–1; Townsend 1979, 62).

The residual welfare model of social policy sees the private markets and family as the main institutions for providing welfare and social security. Only if these two institutions fail in their mission, can the state can intervene. The state support is meant to be short-term and aimed at guiding the beneficiary back to work or to take responsibility for the family. The adjunct welfare model takes social policy as a conciliator between social goals and the private markets. The economy is seen to operate with a logic that without state intervention, markets will create unwanted moral, social and even economical consequences. Basic rights and needs should be secured by the state, but too overwhelming a social policy needs to be avoided, because of the fear it may jeopardise work intensity, entrepreneurship and eventually the economic performance of state. Good economic performance is seen as the necessary condition for the state to practise social policy, meaning that social policy is regarded as a dependent of economic growth. In the redistributive model, social policy is guided by the principle of need. Universal public services and transfers are supposed to provide welfare outside the private market according to the need. The aim of social policy is not just to correct the unwanted outcomes of markets but also to redistribute material well-being, following the principle of social equality.

It is tempting to place this trichotomy next to Esping-Andersen's (1990) classification about the three welfare-state models. Of these the liberal welfare state is said to be guided by the residual model of social policy, the corporatist welfare state by the adjunct model of social policy and the social democratic welfare state by the redistribute model of social policy. However, in reality, no country is located clearly in one single category in either of these trichotomies. We have to remember that these two trichotomies serve us only as a conceptual tool. The classification helps us to see how countries with different ideological, historical and moral foundations can produce social policy arrangements that have far-reaching similarities.

What makes the classification of social policies relevant to the measurement of poverty is that each social policy model has a different understanding of how to deal with a social problem like poverty. And any policy program against poverty has an explicit or implicit explanation of what it is, and why there is, poverty (Townsend 1979, 64). Or better, they usually embody an explanation of the immediate causes of poverty (ib. 62).

The social policy arrangements of the United States correspond well with the residual model of social policy. Old age pensions and health care are dealt with mainly by private insurances and social assistance programs are means-tested and somewhat stigmatising. Residual social policy is inclined to handle poverty as a personal failure, especially if it is a persistent condition. The lack of character and the culture of poverty that the poor have created for themselves is seen as the main reason for persistent poverty. The counterproductive culture of poverty prevents the poor from escaping poverty and they often pass on their counterproductive values and way of living to their children, sentencing them to poverty. So (residual) social policy programs against poverty are often targeted, and means-tested, to strengthen the personal responsibility of the poor over their situation and to weaken the culture of poverty and welfare dependency. Hence, the guiding principle of residual social policy is to help the poor to live without social policy.

The redistributive social policy model regards the responsibilities of the state in a completely different light to that of the residual social policy model. Redistributive social policy sees that the state's responsibility is not just to correct the possible failures of family or markets, but to redistribute welfare that the markets produce on the basis of need and equality. In the 1970's, Sweden came close to the ideal of a redistributive social policy: high level and universal services and social security with almost universal social assistance, together with an egalitarian wage and tax policy aimed to compensate the distribution of income. The causes of poverty in the redistributive social policy model are seen to be in the structure of society and markets. Market forces mean that certain segments of the population are inevitably going to be worse-off and therefore poverty is essentially a structural problem. Alleviating poverty is not seen as the responsibility of a targeted policy program, or even a single policy branch. Poverty is tackled with the whole policy spectrum: with universal social transfers and social assistance, backed up with other policy programs such as employment and housing policy programs.

The adjunct social policy model can be placed in many respects between the residual and redistributive social policy models. The main goal of the adjunct social policy model is to coordinate social values and economic growth, in the respect that social policy is dependent on the economic performance of the country. Social policy arrangements in corporatist welfare states, like in Germany, reflect best the idea of the adjunct social policy model in many respects. The adjunct social policy model perhaps comprises of the most down to earth view on poverty. Policy programs against poverty are designed for the immediate causes like unemployment, illness or old age. Most of the people are considered to be exposed to social risks that can cause poverty. However, how much misfortune is needed to force a family into poverty is dependent on the resources and the life situation of the family.

No matter what the ideal model is behind the social policy of a country, it always needs information about the scale and distribution of poverty within its society. If different models of social policy have a different understanding of what poverty is, they will naturally favour different methods to measure it. Both the United States and the European Union have established their own semi-official poverty thresholds for administrative purposes: the US Census poverty threshold in the United States and the relative poverty threshold in the EU. These poverty thresholds can be seen to reflect a different idea of the purpose of a social policy. The US Census poverty threshold is often referred as an absolute threshold, where a panel of experts define the minimum income level for each size of a family, below which a household is considered poor (see Ruggles 1990). Hence, the US Census poverty threshold is understood to be a minimum income threshold below which, a family cannot function in the society. The European Union has adopted a different way to measure poverty: the poverty threshold is measured as a fraction of average income. This relative poverty threshold reflects the idea that poverty is being too far below the customary living standards and the way of living in the society (see Atkinson et. al. 2002).

We might say that the US Census poverty threshold reflects the ideas of residual social policy model and the EU relative poverty threshold reflects the ideas of adjunct and redistributive social policy models. The EU relative poverty threshold encompasses the idea that poverty and social inequality are bound together. Poverty is seen to have a connection with the income distribution and too large income inequalities causing social, as well as economical, problems. The US Census poverty threshold is, or at least it tries to be, independent from changes in the income distribution. It reflects the idea that poverty and economic inequality are two separate issues and that the latter is not necessarily a concern to public policy.

1.5 Conclusions

We started this introductory chapter by asking three questions: what is poverty, why is there poverty and why should we try to measure it? It was shown that, in contemporary welfare states, poverty is understood to mean relative poverty. Relative poverty is defined as a lack of resources to participate in the activities, and have the living conditions and amenities, that are customary in the society to which one belongs. However, the question of what poverty is is tackled quite superficially, as we return to the definition in the next chapter. Why there is poverty even in affluent welfare states is explained, on a very general level, on one hand by the supported style of living and prevailing living conditions, and the production and allocation of resources on the other. The distribution of resources and the desirable style of living are in constant interaction and together they determine the conditions and expectations of living without deprivation. The answer to the question of why we should study poverty is simple: so that we can do something about it. There are both moral and social justifications as to why we should try to tackle (relative) poverty. Poverty is also a form of inequality that can be seen to cause negative social consequences that, in the extreme, affect the economic performance of the country.

In section three, the historical development of poverty measurement is presented. The measurement of poverty started in the early 20th century with the use of an absolute income threshold for buying food of minimum nutrition. It was not until the 1970s that this absolute income threshold was replaced by the relative income threshold. However, this shift took place mainly in Europe. For example, the US Census still uses the absolute income threshold. Since then the measurement of poverty has expanded, both in scale as well as in diversity. Contemporary sociological poverty measurement has moved towards the use of multiple indicators and longitudinal research settings. The use of multiple measurements means that direct, indirect and subjective indicators are used side-by-side for measuring poverty. The dynamic approach emphasises that poverty is a temporal phenomenon and, for this reason, it should be studied longitudinally using panel data. Multidimensional and longitudinal measurement is presented as the framework in which this study will operate.

Section four shows the close connection between the way poverty is measured and the social policy that is exercised. Each measurement of poverty holds explicitly or implicitly an explanation of what poverty is. For this reason different social policy models tend to favour certain poverty measurements and disregard some others. The residual social policy model, for example, does not favour the relative poverty measure that defines poverty as having an income that falls too far below the average in the society. On the contrary, the relative poverty measure fits nicely with the definition of poverty that prevails in the redistributive (or universal) social policy model, where poverty is understood to be a structural problem, connected to a more general question of equality.

This introductory chapter presented the two main components of poverty research, the definition and the measurement of poverty, and how they relate to a larger social political context. Now we will look in depth at the definition and measurement of poverty in sociological poverty research, which distinctively concentrates on the identification of the poor, and how this is derived from the concept and theory of poverty.

2 The concept and measurement of poverty

2.1 Introduction

To answer the question how much poverty there is within a society, and who the poor are, is not a simple task. Intuitively, we know who the poor are. However, estimates of how many and what kind of people and families live in poverty cannot rely just on intuition. First of all, the estimation of the prevalence and distribution of poverty needs a criterion, or a set of criteria, on which the identification of the poor (from the non-poor) is based and this identification has to correspond to our understanding, or the definition, of poverty. The only correct answer to the question of how much poverty there is, and who is poor, is 'it depends', and it depends, specifically, on two things: how we define poverty and how we measure it.

In this second chapter, we focus on the definition of poverty and how it is operationalised for measurement purposes. After the introduction the definitions of absolute and relative poverty are presented and compared in section two. We will then see how direct, indirect and subjective indicators are derived from the concept of poverty.

Section three moves from the concept of poverty to the actual measurement of poverty. It will show how poverty indicators can be divided into two major categories: head-count classifications and poverty indexes. Then, the different steps of the measuring process will be presented. This starts with the selection of the unit of analysis. Then we will look at the vector of attributes that is measured. Finally, we will discuss how to set a poverty threshold in this vector of attributes.

In the fourth section, it will be shown how a head-count classification can be used in conjunction with other head-count measures in a multidimensional measurement. We will then see how a head-count measure can be turned into a longitudinal measure by using it in repeated measurements. Section five ponders the issues of validity and reliability in poverty measurement, especially in longitudinal poverty measurement. Using panel data brings some additional measurement requirements, because random measurement errors will have a different effect on longitudinal estimates than on cross-sectional. The chapter ends with a summary section that will draw together the main aspects of operationalising the concept of poverty.

2.2 Definitions of poverty

A definition of poverty usually refers to two things: low resources and poor living conditions. This dual reference tries to separate a voluntary modest way of living from involuntary deprivation. In other words, poverty is seen as a condition where there are no resources to escape the situation. Classically, two major traditions for defining poverty have been distinguished: absolute and relative. Rowntree's (1941, 102–3) definition of absolute poverty as a minimum subsistence was one of the first formal definitions and it was the dominant interpretation from the beginning of the 20th century until the 1970's:

> ...(P)overty line represents the minimum sum on which physical efficiency could be maintained. It (is) a standard of bare subsistence rather than living. ... Nothing must be bought but that which is absolutely necessary for the maintenance of physical health, and what is bought must be of the plainest and most economic description.

However, many poverty researchers have pointed out that this absolute (physiological) poverty line is, in fact, relative, since what is needed for a physiological ability to operate within a society is determined by the requirements of that society. This criticism culminated in the 1970's with a fundamental change in the understanding of poverty in the academic and public spheres. Poverty began to be conceptualised as relative - in other words, as inadequate resources to maintain an acceptable way of living in the society in question. This also meant that poverty researchers began to include the inequality of society within their findings since the poverty line was now drawn using the income distribution. Before this shift, poverty was generally seen more as a moral impetus or as an issue involving the maintenance of social order than as an issue of inequality. (Townsend 1971, 2; Townsend 1979, 64.)

The relative definition of poverty is largely accepted in present-day welfare research, although there are researchers, as well as section of the public, who do not support a relative definition of poverty. Perhaps the most well-known and lasting definition of relative poverty was by Townsend (1979, 31):

> Individuals, families and groups in the population can be said to be in poverty when they lack the resources to obtain the type of diet, participate in the activities and have the living conditions and amenities which are customary, or at least widely encouraged, or approved, in the societies to which they belong.

In other words, Townsend defined poverty as relative deprivation caused by the lack of resources. Hence, his definition of poverty is based on the concept of deprivation (see ibid., 413). Since Townsend refined his definition(s), there have been many attempts to present an alternative view. However, Townsend's definition has maintained its central position, in particular, if we understand 'lack of resources' *sensu latiori* as a lack of material *and* non-material resources. The European Union has also defined poverty in relative terms for its policy purposes. The European Council of Ministers decision of 1984 defined the poor as (Atkinson et al. 2002, 78):

> Individuals or families whose resources are so small as to exclude them from the minimal acceptable way of life of the Member State in which they live.

It is not difficult see the similarity between the latter definition and Townsend's. The relative definition of poverty has also received criticism, based both on empirical data and theory. Perhaps the most robust criticism is based on the fact that empirical studies have not found an undisputable threshold in the distribution(s) of resources, below which, maintaining an expected way of living would be not possible. On the contrary, the connections between resources and poor living conditions have been found to be anything but a simple (causal) one. Ringen (1985) especially criticised the assumption that welfare is a function of material resources alone. However, this criticism is targeted towards the problem of establishing a statistical association between resources and poor living conditions. The spearhead of this criticism is pointed to the way poverty is measured, not so much towards the relative definition of poverty.

Sen (1983), on the other hand, emphasised that poverty is not just relative, but also absolute. He defined poverty as a failure to achieve certain minimum capabilities and, according to him, the lack of capabilities is absolute. However, capabilities are not fixed over time or over societies. 'Absolute' in Sen's definition means that there is a threshold in capabilities after which functioning within the society is no longer possible. He criticised Townsend's relative definition in that it did not make an explicit distinction between the different spaces (or dimensions) in which the definition of poverty should be based (Sen 1985). Nevertheless, differences in the space of commodities and resources are relative in the sense that they can produce a qualitative (i.e. absolute) difference in the space of capabilities.

However, how poverty is defined is not as straightforward and clear as it might seem above. In practice, it is often impossible to differentiate between resources, capabilities and living conditions. For example, having no phone or living in an urban ghetto can be seen either as a lack of resources or as poor living conditions. Hence, the conceptual distinction made between recourses and living conditions is not always clear. Constructing an empirical measurement that would guarantee the dual condition of the relative definition of poverty, i.e. that the living conditions are poor because of the lack of resources, has proven to be a very difficult task.

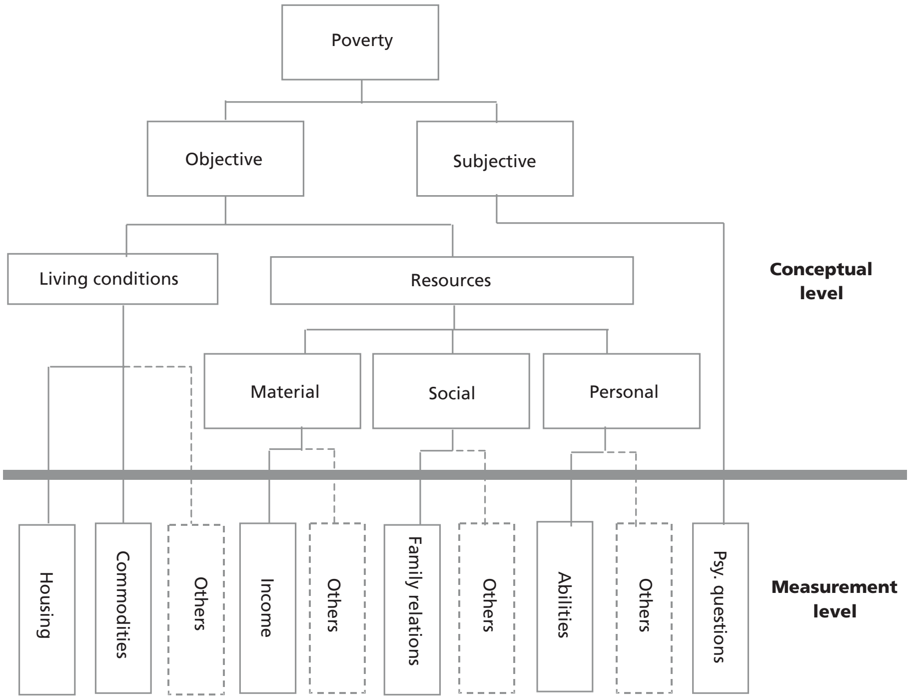

FIGURE 2.1 Conceptual and measurement levels of poverty

Attempts to create a poverty measure that would guarantee the dual condition have not been promising, despite intensive input (see Ringen 1985). Even Townsend could not present an empirical poverty indicator that would have indisputably met the dual condition of his poverty definition (see Townsend 1979, 267; Townsend 1987).

The tree diagram in Figure 2.1 demonstrates how direct, indirect and subjective measures are derived from, or relate to, the concept of poverty. Concept of poverty is at the top and the actual empirical indicators that measure the manifestations of poverty are shown at the bottom, the result of seven choises. The first selection we make in the measurement is, do we measure poverty as an objective or a subjective phenomenon? In other words, do we view that only objectively observable phenomena are valid manifestations of poverty, or is a subjective feeling about poverty enough, or even necessary?

Many scholars do not consider a subjective feeling as a necessary or a sufficient condition for poverty (for example Townsend and Sen), but there are others who argue that the subjective viewpoint can be an important and, even a valid, indicator for poverty (for example Hagenaars). The question 'Are you poor?' would be the perfect indicator of poverty if everybody shared a single understanding of on the acceptable level of well being and used exactly the same verbal description for expressing it (see Hagenaars 1986). Unfortunately for poverty research, people tend to have different ideas of what is the acceptable way of living that should be met and differing views on abstract concepts like poverty. One way to amend this problem is to let the respondents determine 'collectively' what poverty is. In the so-called consensual method(s), the poverty threshold is estimated either (indirectly) by asking respondents what is the minimum amount of money their household would need to make ends meet, or by (directly) asking what consumption items they would consider necessities (see Halleröd 1995). However, the consensual method cannot be taken as a purely subjective measurement anymore, since a person is classified as poor or non-poor regardless her own view. Subjective measures should measure, by the definition, subjective views. So when the manifestation of poverty is measured subjectively, it should be measured with subjective questions, such as: is the household able to make ends meet? Townsend (1979, 418) defined these kinds of subjective questions as measures of subjective deprivation.

When poverty is treated as an objective phenomenon, low resources and poor living conditions are seen as the manifestations of poverty (Ringen 1988). Poor living conditions are often measured with deprivation indexes that are simple sum variables, constructed by summing up the lack of some essential durables or commodities or deficits in housing and the living environment. Resources can be broken down into material, social and personal resources. The lack of material resources is usually measured in terms of disposable income. Social and personal resources, like family relations or health, are not commonly used in poverty research, although they can have a large impact on an individual's well-being. The main reason for this situation is probably the lack of reliable data containing information about social and personal resources. Data on incomes and other material resources are easier to collect and therefore more easily available.

The grey line in the Figure 2.1 separates the conceptual and measurement levels of poverty. There are numerous roots from the top level, that describes the pure concept, to the measurement level. All possible roots are not even presented in the diagram. This shows that there are numerous indicators to measure poverty and none of the indicators is indisputably the best or the right method. It is commonly recognised that poverty has multidimensional manifestations (Atkinson et al. 2002, 78). This multidimensionality brings additional difficulties to the measurement of poverty. One way to circumvent this problem is to simply use more than one indicator to measuring poverty. This is the method we will use in this study. In the next section we will study more closely how the concept of poverty can be operationalised into various head-count poverty classifications.

2.3 Operationalising the concept of poverty

2.3.1 Measuring the poor or poverty

The fundamental division in the field of poverty measurement is between simple head count measurements and more complex aggregated indexes (see Sen 1979). Sociologists generally use simple head count indicators, which identify and calculate the number of poor people and/on families in society. The head count method is usually a sufficient and appropriate method for answering research questions in sociological poverty research. Locating poverty in society is often information that is needed for social political decision-making and administration and head count methods are sufficient for gaining this. More complex poverty indexes are mainly the signature of those economists who are interested in poverty measurement. Simple head count measurements were found to be in the 1970's unsatisfactory for their purposes (Watts 1968, Sen 1976). They started to construct different poverty indexes by combining simple poor/not poor indicators with other indicators that measured e.g. income, among the poor. These aggregated indexes typically seek not simply to count the poor, but also to quantify the extent of their poverty.

Most post-1970's literature in Europe concerning poverty measurement among economists has concentrated on developing these poverty indexes, often together with measurements of inequality like the Gini coefficient[2] or Lorenz distribution.[3] This intensive work has been guided by several axioms that most poverty researchers in economics agree on. Two widely accepted axioms are that (1) the poverty index should increase when a poor person becomes poorer, and (2) the poverty index should be affected only when there are changes in the resources of the poor, but not when there are changes only in the resources of the non-poor (Ruggless 1990, 20). For example, the very popular poverty gap index meets the first axiom and if the poverty threshold in the index is determined non-relatively, then the index also meets the second axiom. The equation for the poverty gap is (Foster et. al. 1984):

---

[2] One of the equation for Gini coefficient is $G = 1 + \frac{1}{N} - \frac{2}{N^2} \sum_{i=1}^{N} (N + 1 + i)(\frac{y_i}{\bar{y}})$, where the N is the size of the sample, i is the rank order of income, y_i is the value of the case and $\bar{y}$ is the mean of y_i . The value of the Gini coefficient lies between zero and one, from total income equality to extreme income inequality. (Creedy 1998, 13.)

[3] The equation for the Lorenz curve is $L = (\sum_{i=1}^{k} y_i)/(\sum_{i=1}^{N} y_i)$, where k indicates those cases where income falls below the poverty threshold. The Lorenz curve shows the relationship between the proportion of people whose income falls below the kth income and the proportion of total income of those cases. In a case of total income equality, a graphically presented Lorenz curve cuts the square diagonally where the axes are the proportion of people against the proportion of income. The curve 'bends' downward as income inequality increases. (Creedy 1998, 17.)

$$P = \frac{1}{N} \sum_{i=1}^{q} \left(\frac{g_i}{z}\right)^2 \qquad [2\text{-}1]$$

where N is the number of total cases, z is the poverty threshold in the (equivalised) income distribution, q is the number of cases who have an income below this threshold and $g_i = z - (income)_i$ is the poverty gap of a household (or a person). The value of the poverty gap ranges between 0 and 1. This value may be used to study how far below the poverty threshold, the income of the poor falls, either in the total population or among different social groups.

The level of sophistication and amount of information naturally increases when using these aggregated poverty indexes when compared to simple head-count measures. However, this increase in information is gained at the cost of comprehensibility. Even researchers who generally use highly aggregated statistical indexes occasionally find it difficult to interpret the source of changes in even the simplest of poverty indexes, such as the described poverty gap. Busy social policymakers with a modest grounding in statistics find it even more difficult to understand complex poverty indexes. From their perspective, the crucial difference between different poverty measurements is the definition of poverty underlying the indicator, not in the details or construction of the indicator (Ruggles 1990, 14).

In this study, only head-count measurements are used and aggregated poverty indexes like the poverty gap or the ordinal poverty measure are only presented as a reference. The reason for this is that most of the influential poverty measurements used in social policy are simple head count measurements. Also, the most crucial error of measurement in poverty indexes is derived from the identification of the poor from the non-poor on which the whole complex construction of the index is based. With simple head-count measurements we can study this error more directly.

2.3.2 The unit of analysis and differences in needs

The first task to fulfil in the head-count measurement of poverty, as in every measurement, is to define the population to which we want to generalize our results. This is not usually difficult; we want to generalize our results to the population where we have drawn the sample, for example, every person in a country. But in the case of poverty measurement, defining this sphere of generalization is not that simple, because it is widely accepted that the family is the most important unit to allocate wealth and the source of welfare to. So, usually in poverty research, income and welfare is measured at the family level, because the distribution of welfare inside the family is assumed to be equal and democratic. The logic of the allocation of welfare inside the family is thus assumed be altruistic and reciprocal. However, this assumption of altruistic allocation according to the needs within the family is not necessarily a valid assumption (Jenkins 1991; Nolan & Whelan 1996, 43.), since we do not have systematic knowledge about distribution within the household.

Therefore, the poverty status of a person is usually determined by the poverty status of his/her family. When using the family as the unit of measurement, we have to make different-sized families with different needs comparable.[4] Because a family's income strongly depends on the numbers of earners in the household, most of the literature on poverty research regarding the ways to make different households comparable is concentrated on how to equalise a household's income according to the needs of the family. A common method for doing this is to use an equivalisation scale to calculate the household's income per consumption unit. The most widely used equivalisation scales for family incomes are the classical OECD scale, the modified OECD scale and the square root scale.[5] These scales can be formally presented as:

$$\begin{aligned} S_i(classic) &= 1 + (a_i - 1) * 0.7 + c_i * 0.5 \\ S_i(\mathrm{mod}ified) &= 1 + (a_i - 1) * 0.5 + c_i * 0.3 \\ S_i(square) &= \sqrt{a_i + c_i} \end{aligned} \qquad [2\text{-}2]$$

where a_i is the number of the adult members in the *i* household and c_i is the number of children in the *i* household. For example, in the modified OECD scale, every additional adult increase the weight by 0.5 and every child by 0.3. Dividing the household's net income by the coefficient of the equivalisation scale gives the disposable income per consumption unit. The logic behind the use of equivalisation scales is that a bigger household has more needs than a smaller household and an adult has more needs than a child. Weighting bigger households and households where there are more adults is a method by which to estimate the quantity of the needs of a household. A family is also assumed to gain advantage of scale in large purchases. This is why (usually) the equivalisation scale is not calculated simply by dividing household incomes with the number of (adult) family members. Also, families with children are seen to need more income to achieve the same well-being than a family without children since children increase the needs of, and bring new needs into, the family. But in the end, equivalisation scales are more

[4] This is an issue that needs to be resolved especially if we measure poverty as a lack of resources. This is not such a problem when poverty is measured as poor living conditions or as a subjective view. Durables that are considered as essential or the level of accommodation, for example, can be defined in such a way that comparison between families is possible. However, households do have different needs according to their size and composition, living area, etc., so that defining what living conditions are too low for different kinds of households can be difficult. And, with the subjective view of poverty, the problem is whose subjective views in the household are taken account and who's are not.

[5] To calculate expenditure per consumption unit, there are very similar equivalence scales (e.g. Pollak & Wales 1979), but they are less widely used, which reflects the fact that family expenditures are rarely used in the measurement of poverty. One reason for this is that detailed and reliable information on consumption is not readily available compared to data on household incomes.

assumptions and agreements than a result of empirical studies or theoretical derivations.

By dividing a household's incomes by an equivalisation scale, we get the income per consumption unit in the household, which is a standardised and comparable income unit which can be used over different sizes and types of households. The equation for calculating the equivalent income for the *i* household can be presented as:

$$C_i = \frac{I_i}{S_i} \qquad [2\text{-}3]$$

where I_i the is the total net income of the *i* household and the S_i is the number of the family's consumption units, calculated using an equivalisation scale in [2.2]. A household is then classified as poor if its equivalent income falls below the poverty threshold F_p, set usually by a function of the distribution of equivalent income C_i. Often the function is 50% or 60% of the median. For example, the recommendation of Eurostat is 60% of the median threshold and the OECD modified scale. This relative financial poverty classification can be presented formally as:

$$\begin{aligned} C_i &\geq F_p(= 0.6 * Med(\frac{I_i}{S_{i(\mathrm{mod}\mathit{ified}}})) \Rightarrow \mathit{nonpoor} \\ C_i &< F_p(= 0.6 * Med(\frac{I_i}{S_{i(\mathrm{mod}\mathit{ified}}})) \Rightarrow \mathit{poor} \end{aligned} \qquad [2\text{-}4]$$

Naturally, it is possible to calculate different financial poverty lines for different kinds of households and this way avoid using an equivalisation scale. (Actually, this matrix of poverty thresholds would be its own equivalisation scale.) For example, the very influential US Census poverty threshold is a matrix of financial poverty thresholds, presenting a real dollar amount threshold for each type of family (Poverty in the United States: 2000, 5). This method has not gained the same popularity in Europe as the equivalisation scales, although perhaps only for practical reasons: equivalisation scales are easier to use and interpreting one poverty line is quicker. However, if we calculate the poverty thresholds in real euros for different sizes and types of households using the modified OECD scale, we can see that the matrix of financial poverty thresholds is very similar with the matrix used by the US Census. In other words, the modified OECD scale and the US Census poverty threshold matrix seem to give almost identical weights to the same size and type households. Differences become noticeable only when family sizes increase, but since the majority of people live in relatively small households, we can say that the OECD modified scale and the US Census poverty threshold weights the needs of different sizes and types households very similar way.

There is extensive literature proposing different techniques, several more than presented here, to standardise a household's income according to its needs (Nolan & Whelan 1996, 44–7). However, most equivalisation scales are based on the same assumptions and formulations as the scales presented in [2-2], where adults have a heavier weighting than children. (For a review on equivalisation scales used in different countries, see Atkinson 1995, 80–1: Citro & Michael 1995, 167.) There are several studies showing that a selected method for adjusting a household's income to its needs has a substantial effect on financial poverty figures. Different households can be identified as (income) poor depending on the kind of equalisation scale that is used. The decision of Eurostat to change the old OECD scale to the modified OECD scale has caused much debate, both among scholars and politicians (see Ritakallio 2002). Although the new equivalisation scale does not change the poverty rates or the rank order between the EU countries much, it changes the distribution of poverty in the population. By giving less weight to households with children and larger households in general, the modified OECD scale gives lower child poverty rates but higher poverty rates among single households than the former OECD equivalisation scale (see equations in [2-2]).

One way to resolve the problem that is caused by different results depending on the equivalisation scale used, is to carry out so-called sensitivity analysis, where financial poverty lines are calculated using different equivalisation scales and then the results are compared (see Atkinson 1998, 37–41). But the main problem still remains: the difficulty in estimating the needs of different kinds and sizes of households. This difficulty may also be why so many poverty researchers favour poverty indicators that identify poor households directly from poor living conditions. This, however, simply changes the name of the problem. The question of need is now presented the other way around: what are the adequate standards of living for different kinds and sizes of households? For example, a car can be considered a necessity for a person with a disability living in the countryside, but for a single adult living in a city, a car can be more of a nuisance than a necessity. So, the needs of the household determine the amount of resources, but also to some degree, the level and the quality of living conditions that is needed to live without deprivation.

2.3.3 Direct, indirect and subjective measures

In order to identify the poor, we naturally need an indicator that indicates those who are poor. Hence, we need a measure that can be said to measure a manifestation of poverty. The best poverty indicator would be, of course, one that would (1) classify those and only those as poor who really are poor and (2) have plausible theory to explain why the measured phenomenon occurs only if, and when, the subject is poor. As was discussed earlier, an indicator like this does not exist. The actual measurement of resources, living conditions and a subjective viewpoint is a difficult task. However, three types of indicators have secured their position in poverty research. These indicators measure either low resources, poor living conditions or a subjective view of deprivation as the manifestation of poverty. These three groups of poverty indicators were presented already in figure 2.1 and these groups are often called direct, indirect and subjective measures.

Measurements that use low resources as an indication of poverty – measured either as income or consumption – are often referred to as indirect measurements of poverty (Ringen 1988). Indirect poverty measurements are probably the most widely used when determining whether a household is poor or not. In indirect poverty measurement a household's[6] available material resources, usually the disposable income per consumption unit, are estimated and if they fall below a specific threshold, the household is identified as poor. A detailed definition of disposable income can be very long, but disposable incomes can be defined in general terms as income that is left under a household's control after income taxes and social insurance contributions from salary and self-employment earnings, capital and other non-work private incomes and social transfers. Indirect poverty indicators that use the distribution of income to identify the poor are also called as financial poverty indicators.

Measuring the actual use of material resources, in other words, measuring poverty as low expenditures or as a low consumption, is technically similar to measuring financial poverty (see Jäntti & Danziger 2000, 319–20). There are some advantages and disadvantages in using low consumption to indirectly measure poverty, however. One strength of estimating poverty status from low expenditures is that, for example, huge variations in housing costs between regions and countries can be taken into account. However, reliable data on household expenditures is not as easily available as data on household incomes and this is probably the main reason why indirect poverty measurement based on low expenditures is not frequently undertaken.

'Indirect' refers to the fact that these indicators measure poverty indirectly, in other words, they measure the lack of resources that is assumed to cause deprivation. Indirect poverty measures have been criticised for assuming that welfare is a function of material resources. Several empirical studies have shown that the correlation between low material resources and poor living conditions is complex. This criticism culminated in the 1980s when Ringen (1985) published his influential article, pointing out the logical break between the relative definition of poverty and the indirect poverty measures that where supposed to be operationalisations of the definition. Ringen suggested that poverty should be measured directly as poor living conditions.

[6] The unit of measurement is not always, and does not necessarily have to be, a household, but it is the most widely used (see previous chapter) and for the sake of clarity, it is used here consistently.

Measuring poor living conditions as the manifestation of poverty has gained much popularity since the 1980s. There are two probable reasons for this. First, there is a logical break, as Ringen pointed out, in measuring poverty as a lack of resources but at the same time defining poverty by referring to poor living conditions. Secondly, empirical studies have shown that a household's disposable income is a weak predictor of deprivation, i.e. that there is a weak overlap between those households identified as income poor and households identified as having poor living conditions (e.g. Hansen 1987, 166–7). This is usually interpreted as a weakness of indirect measurements. Several deprivation indexes have been developed for directly measuring poor living conditions to identify the poor. Most of these indexes are simple sum variables, calculated from a set of dummy variables, in which each variable indicates the lack of some essential consumer durable, problems with accommodation, etc. (e.g. Mack & Lansley; Townsend 1987).

Both indirect and direct poverty measurements are called objective poverty measurements, since it is the researcher who makes the judgement on whether the household is poor. This does not give the informant/respondent the chance to give his/her own interpretation of his/her situation. Thus, the third type of poverty measurement uses the informant's subjective perception on her financial/material situation as the indicator of poverty. The sphere of subjective indicators includes all possible ways that the subjective view of being poor or deprived can be measured. A very popular method is to ask the household if it is able to make its ends meet every month, but there are several other question patterns for measuring the subjective view of deprivation (see Piachaud 1987). Also social exclusion has been measured with subjective measurements (e.g. Heikkilä & Sihvo 1997).

In fact, the question 'Is your household poor?' would be the perfect indicator of poverty if everyone shared one understanding of the minimum level of well being and they would use exactly same verbal description for expressing it (see Hagenaars 1986). However, people tend to have different ideas, for example, on what is the minimum level of well being that should be met, and also a different understanding of abstract concepts like poverty. For these reasons, subjective deprivation measurements have been criticised. Also, many people do not consider a subjective view to be a sufficient or a necessary condition of poverty (e.g. Sen 1977). However, figures of subjective feelings of deprivation give valuable information on the satisfaction of people, and also, valuable information, against which information from the objective poverty measures can be compared.

One possible solution to the disagreement as to the best method of measuring poverty directly, indirectly or as a subjective view is simply to use direct, indirect and subjective measures side-by-side. This means measuring poverty with more than one head-count indicator. It is generally acknowledged that different indicators give differing pictures of poverty. To correct this problem, we could use all the three types of indicators together side-by-side, without any attempts to aggregate them, and in this way gain a more comprehensive and reliable picture of poverty. This will be the method applied in this study.

2.3.4 Poverty threshold in a distribution

The final decision be made when constructing a head-count poverty measurement is to determine where to set the poverty threshold in a distribution of resources, living conditions and subjective views. The cut-off point will divide households into poor and non-poor according to their score in the selected distribution. How the poverty line is determined in the actual and final measurement situation can be categorised into three types: the use of a function, the use of a fixed threshold, or the use of multiple criteria. In practice, all three methods often influence the judgement simultaneously. Thus, these methods of setting the poverty threshold are more like ideal types, not exclusive categories.

When the poverty line is defined as a function of a distribution, the attributes of a sample will determine the place where the poverty line is set. In most cases, this poverty line is a function of the income distribution. For example, the relative financial poverty threshold of the EU, which was presented earlier, determines a household's poverty status by using 60% of the median income of all households as the poverty threshold.

A fixed poverty line is set before measurement, using (additional) information from outside of the sample. Experts, administration, etc. decide this fixed poverty line. At the national level, the most influential fixed poverty line is probably the income threshold where low income households are identified as poor when they are for eligible (because of their inadequate income) for means-tested social assistance.[7] Another influential fixed poverty line is the U.S. Census poverty threshold, which is defined as the minimum amount of money that a family has to spend on food multiplied by three, because it was estimated that families spend one-third of their net income on food (Citro & Michael 1995, 24).

The poverty line can also be judged as an intersection or an accumulation of fixed and/or function thresholds. This type of threshold can be called the multiple criteria threshold. A well-known example of multiple criteria for setting a poverty line is Townsend's dual-condition poverty measurement, where the poverty threshold is the intersection in the income distribution after which deprivation starts to increase rapidly. The multiple criteria method is also used when the poverty threshold is defined as the overlapping of poor living conditions and resources (e.g. Goodin et. al. 1999, Nolan & Whelan 1999). Eurostat's (1998) measurement

[7] However, social assistance erases or at least is supposed to erase poverty. Because of this, receiving or not receiving, social assistance is a problematic classification when used in conjunction with other poverty measures.

of multiple problems with accommodation (accumulated housing deprivation) can also be viewed as a poverty measurement with a multiple criteria threshold.

Naturally, this classification does not fit the reality perfectly: all poverty thresholds are more or less dependent on some average level in society, fixed beforehand and based on several criteria. For example, even the material resources needed for minimum nutrition is dependent on the society at hand, since the threshold also depends on the average living costs in the society. Also, these categories are not clearly exclusive or exhaustive and categorising them is meant to be a rough simplification of the different ways of setting poverty thresholds. There are several alternative methods to determine the poverty threshold in a distribution of resources, living conditions and subjective statements (see Kangas & Ritakallio 1998, 170).

2.4 Measuring poverty as longitudinal and multidimensional phenomenon

2.4.1 Measuring poverty as a multidimensional phenomenon

A measurement device is the tool that is used to translate an observed phenomenon into the language of statistical mathematics. In doing so one has to justify that the scale corresponds with the measured phenomenon and that the measurement device is reliable and valid. Sometimes this justification is easy. For example, when classifying people according to their gender, the scale is a dichotomy and it is easy to construct a valid and reliable measurement device. The survey question 'are you male or female?' with two choices of answer 'Male=1, Female=2' is a reliable and valid measurement device for the classification. The value one is then treated as value that one has if (and only if) one is a man. The small number of misclassifications are due to measurement error when a woman (or a man) has marked the value one (or two), because of carelessness or just for fun. This is an example of one-dimensional measurement, where there is no uncertainty about the vector of attributes that is measured (man or woman) and there is a simple, reliable and valid measurement device for measuring it.

However, phenomena that interest social scientists are often complex abstractions, like social class, mobilisation – or poverty. They are difficult to observe, not to mention measure, directly. The conceptual construction of terms like poverty or class is often like a tree diagram, where the actual (supra) concept is on the top, related to subconcepts via theoretical derivation. Usually in the practical measurement situation, the supra-concept can be measured only by operationalising its subconcepts. For example, poverty is usually measured by operationalising the lack of resources, poor living conditions or the subjective view of deprivation. This results in a set of different indicators, where each indicator measures poverty from a different angle and none of the indicators are indisputably better than the other.

Hence, the simple question, 'are you poor?' is not necessarily an adequate device for measuring poverty. Although most of us agree that a subjective view is part of what is understood by poverty, nevertheless, few would argue that a subjective view is a sufficient or a necessary condition for indicating poverty. Other aspects of poverty need to be measured, like lack of resources or poor living conditions. This observation points towards the idea that more than one indicator should be used, perhaps side-by-side, for the satisfactory understanding of a multidimensional phenomenon like poverty. This is why many believe that poverty should be measured together with direct, indirect and subjective indicators so that each indicator can give complementary information on the differing aspects of poverty.

Hence, all the methods for classifying households to the categories of poor or non-poor, are hampered by difficulties in actually measuring things like low income, poor living conditions, low consumption, the subjective view of poverty and so on. The most disturbing consequence of these problems of classification is that quite different groups are identified as poor by different methods and poverty indicators (e.g. Atkinson 1998, 11). One solution is to treat different methods and indicators as complementary methods for gaining information on a social problem that has multidimensional character.

So after two decades of dispute between different schools on how poverty should be measured by one 'true' indicator, the trend in present-day sociological poverty research is towards multidimensional measurement. Multidimensional measurement is carried out with a set of head-count indicators that include direct and indirect measurements as well as possible subjective indicators (see Muffels et al. 1992; Kangas & Ritakallio 1998; Bourguignon & Chakravarty 2003; Moisio 2004). Hence, poverty is measured using several indicators side-by-side, without an attempt to aggregate them into one index. On the contrary, there are as many estimates for poverty as there are indicators. Thus, poverty is defined as a multidimensional phenomenon, and different ways to measure poverty are seen as alternative ways to gain complementary information on the same complex social phenomenon. In the multidimensional approach it is accepted that one estimate or index cannot give a satisfactory picture of poverty.

2.4.2 Measuring poverty as a longitudinal phenomenon

Alongside the realisation that poverty can be multidimensional, it has also become acknowledged that poverty should be analysed as a longitudinal phenomenon. Taking the temporal aspect into consideration is seen essential both to understand poverty and for the development of a social policy (Bane & Ellwood 1984). The changing view of poverty from a static condition to a dynamic process is perhaps connected to the debate around social exclusion which took place in Europe around the turn of the millennium. In the United States, longitudinal poverty research has flourished. Poverty has been treated in the US, both in politics and academic research, more explicitly as a temporal and dynamic phenomenon. Concepts like the underclass or the culture of poverty, which have always been more popular in the US than in Europe, emphasise the temporal nature of poverty. The European Union and Eurostat have recognised the need for longitudinal poverty research in Europe and as a response to this need, a large EU-level household panel called the European Community Household Panel (ECHP) was launched in the mid 1990s.

There are three aspects in longitudinal poverty that can be studied, according to Jäntti and Danziger (2000): (i) the duration of poverty, (ii) the distribution of poverty spells in the population and (iii) the likelihood of future poverty spells. Walker (1994) described the time dependent nature of poverty by four dimensions that determine the pattern of poverty statuses over time: (i) the volatility and stability of poverty statuses over time, (ii) the extent of recurrent poverty, (iii) the length of poverty spell and (iv) the length of the observation period. In other words, the distribution of poverty over time can be described by information on the prevalence, periodicity and duration of poverty (Fouarge & Layte 2003).

The term poverty mobility is used to describe the process where people and families enter poverty and, after a certain time, usually exit poverty. Poverty mobility occurs in two ways. First, families cross the poverty line because there is a change in their resources or in their needs so that the household falls in poverty, or exits poverty. Secondly, the poverty threshold itself can change and families who have not been considered as being in poverty before are now classified as poor, or vice versa. The latter type of poverty mobility, i.e. caused by movement of the poverty threshold, is perhaps only an issue if we use a poverty threshold that is a function of a distribution, along with the use of a very long follow-up period. Over a relatively short time period – years not decades – the annual fluctuation of a function poverty threshold is quite small, reflecting the fact that the shape of a distribution (e.g. income) changes slowly within the population. So it is quite safe to say that most poverty mobility is caused by changes in the resources, or the needs, of a household, or both.

Studies have shown that in many cases, changes in household incomes and living conditions are due to changes in the size and composition of the household itself. For example, almost a half of entries into poverty in the US are preceded by a demographic change in the structure of the household, such as divorce or an addition to the family. However, less than 20 per cent of exits from poverty are preceded a demographic change in a household. (Bane & Ellwood 1986; Jenkins 2000.) This is why studies of poverty mobility focusing only on individuals instead of families maybe be misleading. For example, income mobility studies usually follow individuals and the changes in their personal incomes. Poverty, on the other hand, depends also on the individual's household context (Bradbury 2001, 53).

Another empirical finding is that movement into, and out of, poverty is very common. For example, in the EU only about one half of the income poor were poor in the previous year. (Layte & Whelan 2003). This high mobility results on the proportion of population living in long-term, uninterrupted poverty being much lower than the proportion in poverty at any given moment. On the other hand, there are two to three times more people experiencing poverty in the last, say, three years than there are people classified as poor at any given moment (e.g. Krause 1998). Bane and Ellwood (1986) had similar results in the US with a longer follow-up period. They found that the most of the people who experienced poverty were in poverty only for a short period. However, their analysis discovered that the probability of their exiting poverty drops sharply the longer the period of poverty lasts.

Whelan et al. (2000) have shown that cross-sectional poverty rates and the level of poverty mobility, do not have any consistent relationship within the EU countries. Aber & Ellwood (2001) came to the same conclusion between child poverty mobility and cross-sectional child poverty rates in the US and Europe. Whelan et al. (2000) also analysed two-way poverty transition tables with log-linear models and discovered that many EU countries have surprisingly similar patterns of poverty mobility, despite the differences in the poverty rates and persistent poverty rates (measured as being poor for two succeeding years).

Some researchers have studied poverty spells, which is the time spent in poverty. Analyses of poverty spells are often done with Cox regression -type models, where time is included in the linear model as a continuous variable. These models are then used to study various elements, for example, how the probability of exiting poverty develops by the length of the poverty spell (Hill 1981) and the characteristics of the households who exit and do not exit poverty (Bane & Ellwood 1986). The main findings of these analyses have been, as was mentioned earlier, that the probability of exiting poverty drops sharply the longer the duration of the poverty spell and that events preceding poverty exits and poverty entries are not 'mirror images' of each other.

Repeated poverty classifications have also managed to somewhat alleviate the problem of little overlapping between different head-count poverty measures. The fact that different poverty indicators identify quite different parts of the population as poor is seen a serious problem with the reliability of poverty measurement. Gordon (2002) has suggested that the dynamic approach to the measurement of poverty can solve the much-debated problem of a small amount of overlapping between financial poverty and deprivation classifications. He suggests that low income develops into deprivation with a certain period of delay. Because of this delay, many people who are classified as poor according their (household's) income are not (yet) classified as having poor living conditions. And when the financial poverty spell ends, living conditions will rise with a period of delay. This means that those who have just exited financial poverty, and so classified as non-poor according their (household's) income, are still classified as deprived according their living conditions.

There is also empirical evidence which shows that longitudinal measurement is a more valid and reliable way to measure poverty than cross-sectional. Whelan et al. (2002) discovered that turning head-count poverty classifications into longitudinal measurements increases the overlapping between the groups identified as poor by the indirect and direct poverty measures. Hence, we can treat longitudinal measures not only as a more valid measurement (they correspond better to our understanding poverty as a temporal process), but they also seem to be more reliable than their cross-sectional counterparts.

2.5 The validity and reliability of poverty measurement

2.5.1 Discrete and categorical scales

When we attach numbers or symbols to the answers or attributes of studied objects, we also adopt some perception of measurement. And, in the case of head-count poverty measurement, that is understood as a qualitative classification, this means categorical variables. How these are perceived determines the types of operations we believe that we can perform with these numbers, or symbols, and how we define the error of measurement. The former is connected to the question of the scale of measurement, the latter to the validity and reliability of measurement.

Usually the question of scale is detached from the validity of the measurement, although selecting a justified and correct scale is the first step towards validity. However, this traditional separation is followed by the order of presentation here. The question of scale, i.e. what kind of (mathematical) symbols we use for describing a measured phenomenon, is often by-passed in the social sciences. However, the scale is our attempt to describe some of the attributes of the object one-dimensionally. In other words, we translate one attribute of the observed phenomenon into the language of mathematics by attaching some symbols to the observations. We define a measurement model for this observation converted into a one-dimensional scale. For the conversion, there must be a scale which corresponds to our observations and common sense. A higher-level scale will make use of more sophisticated statistical methods possibly, but the only principal for defining the scale of measurement should be the justifiability of how the scale describes the vector of the observations. This scale selection will then determine what kind of a measurement model we can construct for measurement purposes.

Traditionally, four different levels for the scale of measurement have been presented: nominal, ordinal, interval and ratio scales. If the one-dimensional attribute that is measured can be only classified into different categories, e.g. red, blue, yellow etc., the only reasonable scale is nominal. Then we can attach symbols to these categories, e.g. R, B, Y, etc., or 4, 2, 5 etc., If we can organise these categories into some order, for example if red, blue and yellow describe the colours of healing wounds in different stages, then attached numbers have to describe this order between these stages of healing, for example, I, II and III. If the observed one-dimensional attribute has some standard measuring unit between the categories, for example, it takes 2 days for a red cut to turn to blue and from the blue colour it takes 7 days for the wound to turn yellow, then we can describe this phenomenon with an interval scale. The highest scale, ratio scale, can be used only for describing a vector of attributes that has an absolute zero point, i.e. a point in the vector of attribute where the measured attribute does not exist. In the ratio scale we can divide the score by another score and say that the first object possesses the attribute, for example, four times more than the second one. (Bollen 1989.)

The biggest difference in interpreting scales is between nominal scales and other scales; in other words, the difference between taxonomies and traits (dimensions, vectors etc.). Taxonomies differ from other scales in that the object has, or does not have, the measured attribute: in other scales, objects always have some quantity of attribute. The absolute zero point in ratio scales is an interesting exception, but in the social sciences we can overlook this. There are few cases (e.g. weight, height and age) in the social sciences where ratio level scales can be used, but interval level scales are commonly treated in the same manner as ratio scales. However, it is usually difficult to justify the comment that observations in the social sciences are more than ordinal. Sometimes this can be a problem, sometimes not. A commonly accepted criteria for selecting a scale is that researchers should always be able justify the scale that they use to describe a measured attribute.

The second question raised when defining the scale of measurement is whether the vector of attributes is construed from some fixed amount of possible values. In other words, does the measurement produce only specific values or can it have an indefinite number of values? The former variable is discrete and the latter is continuous, and drawing distinctions between these two can be troublesome. “Observations tend to be discrete, even when we think of properties that we conceive of as continuous" said Andrich (1988, 11), referring specifically to measurement situations in the social and behavioural sciences. For practical reasons, we are usually forced to measure observed scores by some type of restricted and/or discrete scale.

There are two different epistemological foundations for understanding categorical and discrete variables. Powers and Xie (2000) labelled these approaches as the biometric-statistical approach and the psychometric-econometric approach. The biometric-statistical approach believes that discrete variables are essentially discrete and that an observed discrete vector corresponds to the measured phenomenon, or the latent structure that describes the measured phenomenon or process. The psychometric-econometric approach, on the other hand, assumes that observed discrete variables are simply imperfect reflections on an essentially continuous latent variable, or imperfect reflections of some other latent structure with continuous variables, that observed discrete/categorical scale(s) cannot reflect perfectly. (Agresti 1990, 26–7; Powers & Xie 2000, 8.)

The biometric-statistical approach shows that mathematical symbols correspond, and have to correspond, to the attribute that is measured. In other words, the scale of measurement perfectly represents the vector of attribute that is measured and the measurement error causes a mismatch between observed scores and measured vectors of attributes. The transformation of variables, like probit or logit transformation from a dichotomous response variable, is a common technique in this approach, to make categorical variables meet the assumptions of statistical models. Another method is to use a measurement model, where the structural part of the model represents the discrete/categorical space (and time, if the structural component represents a process).

In the psychometric-econometric approach, discrete variables are seen as incomplete measurements of an originally continuous phenomenon – variables are discrete (or categorical) only because we cannot directly measure the 'latent' distribution that we actually want to measure. For example, the Likert Scale scores are seen as an imperfect reflection of the continuous distribution that runs from extreme negative to extreme positive opinion. Respondents are simply forced to roughly select a possible proximity from given points in this latent distribution. The probit model is often given a similar interpretation: the model presents a dichotomised version of an underlying normally distributed continuous variable.

The question regarding what the vector of attributes is that a categorical variable measures is very important in the measurement of poverty, since a head-count poverty measurement is seen to represent a real, qualitative distinction between the poor and non-poor, at least in theory. But many direct poverty measures, like deprivation indexes, assume that the observed discrete scale is reflecting a latent continuum. However, the question about the relationship between the scale of measurement and the scale of the vector of attributes cannot be answered here in depth, as it would require another book. For those interested in these questions, we recommend turning to the cited literature in this section.

2.5.2 Validity of poverty measurement

Validity is the concept used to describe whether the interpretations made from the measurement are reasonable; hence, it is a concept that is more robust than the reliability of the measurement. Traditionally, in the classical test theory, reliability and validity are treated as separate issues: the validity of the measurement is judged rhetorically outside the actual measurement situation and the error of measurement is seen as a problem concerning the measurement device (Standards for educational and psychological testing 1994). Usually four types of validity are distinguished: content, criterion, construct and convergent validity. Content validity is a qualitative type of validity where the analyst judges whether the measure fully represents the theoretical definition that explains the meaning of the concept. Criterion, construct and convergent validity are considered to be empirical methods by which to test content validity. (Bollen 1989, 185–94.)

There is no way to assess the criterion validity of poverty measurement since there is no standard or 'official' poverty indicator to which to compare our measure.[8] However, we can review the construct and convergent validity of poverty measurement. Construct validity can be scrutinised by using a reliability coefficient, like the Cronbach' alfa-coefficient, when summed variables are constructed. The construct validity of summed poverty and deprivation scales are usually low. Similar results can be attained when scrutinising the convergent validity of poverty measurement by, for example, observing whether different poverty measurements identify the same people as poor.

However, nowadays 'calculating' or 'proving' validity has become rarer, since it has been found that it is impossible to argue validity purely by means of statistical mathematics. Instead, validity is increasingly seen as the attempt to create a reasonable, well-grounded and clear heuristic construction that justifies the measurement used and places it in relation to other measurements and theories (Moss 1992, 238). So we can argue that the use of multiple indicators and longitudinal data improves the (content) validity of poverty measurement. Poverty is understood as a temporal phenomenon, which is defined as a lack of resources to achieve preferable living standards. By measuring the lack of resources and living standards (and also the subjective view) longitudinally, our measurement device corresponds better with the temporal and multidimensional phenomenon that is measured, than a measurement device which gives a static one-dimensional snapshot. This way, a multidimensional and longitudinal measurement can be viewed as a more valid way to measure poverty than a static one-dimensional measurement.

[8] In economics, however, a kind of 'aggregated' criterion validity is often presented for individual and household incomes: the aggregate of these incomes should correspond to national accounts.

Costner (1969) and Blalock (1968) emphasised that when measuring abstract social concepts,[9] like class, political opinion or poverty, one should always make a difference between the empirical measurements that are used for measuring the abstract phenomenon, and the actual abstract conceptual construction that is supposed to be measured. They suggested that we should always make two empirical decisions when measuring abstract concepts in sociology. First, we must evaluate whether the empirical measurements are adequate and valid indicators for measuring the abstract formulation. Second, we must evaluate whether the abstract formulation is itself tenable. This can be done by separating the measurement part and the structural part in the model, and then building a theory that explains why these two components of the model relate to each other in the way they do. The measurement part of the model describes how the empirical measurements relate to the structural component of the model. The structural component is the abstract conceptual/causal construction that we can assume to be measured imperfectly with the observed measures.

2.5.3 Reliability of measurement

Even if we could manage to construct the perfect poverty indicator derived from the perfect definition of poverty, i.e. the indicator would have perfect validity, we could still never perfectly measure poverty. The measurement situation will always contain random and unexpected factors, from coding errors to the misinterpretation of a question in a survey, which causes unsystematic variation in observed scores. This is the reason why in contemporary textbooks on measurement theory, writers often do not separate validity from reliability, although reliability has been, and is still considered to be, a problem of measurement device.

Since a certain amount of measurement error is unavoidable, even with a perfectly constructed indicator, we need a sophisticated method to deal with the error of measurement. The most appropriate method is to create sets of parallel measurements designed to reflect unsystematic variation, i.e. random error. Parallel measurements are a set of indicators that measure the same phenomenon; in other words, parallel measurements are operationalisations of the same concept. Because parallel measurements measure the same latent referent, an unsystematic variation from one measurement to another can be estimated and thus gain a quantitative description of the error of measurement. Also, the expected value, or mean, of parallel measurements is treated as the estimate of the 'true value'.

[9] Psychometricians would talk of Platonic and non-Platonic (or classical) measurements, where the former refers to the measurement where a true value is plausible, like physical measurement, and the latter to measurement where the true value is (empirically) implausible, like attitudes (Biemer & Stokes 1991, 489).

The test-retest method is one very common technique in the natural sciences to create a set of parallel indicators. Unfortunately, to retest with exactly the same measurement conditions is usually impossible within the social sciences; first of all, an informant can change between measurements, unlike a physical object. This why in social and behavioural sciences, parallel measurements are in fact always gathered with several parallel indicators side by side in a single measurement.

The most influential measurement theory in the social and behavioural sciences is the classical test theory (or classical true score theory), which holds certain assumptions concerning measurement, rules of inference and methods for studying the reliability and evaluating the measurement error (Ghiselli et. al. 1981, 195). In classical theory, an observed value is expressed as the sum of the true value T_i and measurement error E_i. This can be presented as the 'basic' equation of classical test theory;

$$X_i = T_i + E_i \qquad [2\text{-}5]$$

The equation 2-5 defines every observed value in the case of *i* as the sum of the true value and the measurement error. The classical theory also holds axioms that the mean of measurement errors is zero $(\overline{E} = 0)$ and that the true value and the measurement error are independent. So the expected values of the true and observed values are assumed to be equal $(\overline{T} = \overline{X})$. The axiom $\overline{E} = 0$ also means that the classical test theory assumes that all measurement error is random error and no systematic error (bias) where $\overline{E} \neq 0$ is present in the measurement situation. This is often not a valid assumption. Also, in practice, one cannot separate the true value and the error, but there are ways to estimate these two components. The most common practice is to create a set of parallel measurements that each measures the same concept. The unsystematic variance between these parallel measurements then provides a quantitative description of the measurement error.

The reliability of poverty indicators is, and has always been, rather questionable. Usually the overlap between different poverty indicators is quite small. Although the overlap increases when the observation period is extended, for example, Jeandidier and Kop (1998) came to the conclusion that even with longitudinal poverty measures there are three different dimensions of poverty, or three different poverties. So if one wants to study the reliability of poverty indicators, one should study it within each dimension of poverty. However, what these dimensions are and what their limits are remain somewhat unclear. This is why reliability analyses with poverty indicators are open to various interpretations. In the following, we ponder the reliability of direct, indirect and subjective measures separately and this way we assume that these three types of indicators measure different poverties – or different dimensions of poverty.

The error in survey data falls roughly into three categories: errors of non-observation, processing errors and measurement (or observational) errors. The errors of non-observation arise from nonresponse, coverage and sampling. Processing errors arise from the coding and classification of data, imputations and other processing of data. The measurement errors can have four sources: the interviewer, the questionnaire, the mode of data collection and the respondent. (Groves 1991, 2–3.) Errors arising from non-observation, data collecting and processing were minimised with standardised techniques in surveys. Measurement error arising from the respondents is perhaps a more complex issue. Respondents' different personal characteristics, perceived values and norms associated with particular answers, abilities, socialized identification and reference group and their state of mind cause random and often systematic error in their answers for standardised questions (see Del Boca & Darkes 2003).

We can expect respondent's answers to the questions relating to their incomes, household structure, living conditions and subjective feeling about economic strain to contain at least random measurement error, but also, in all likelihood, systematic error. With subjective questions the reference group might be the most prominent source of measurement error. With the subjective questions, it is (implicitly) asked that the respondent compare her situation to the situation of others. Respondents most likely use different reference groups when evaluating their living conditions, or make a value judgement as to whether their household has reached 'adequate' living conditions (see Townsend 1979, 426; Whelan et al. 2001, 368). With objective deprivation measures, this restricted reference-group problem is circumvented by asking a list of questions on the possible lack of some basic commodities and defaults in housing. However, the items that are seen as necessities by the researcher (or by the general population) are not necessarily the same as the respondent's. The respondent may spend her money on items she prefers and due to this, lacks resources to obtain items deemed as necessities in the survey (ibid, 358).

When measuring financial poverty, the respondent-related error can be either due to respondents reporting wrong information about their incomes and/or their household's size and composition. The respondent may forget or knowingly not report some components of their household incomes, especially if these incomes are small and irregular, or as a result of the black economy. Also, surveys request incomes to be reported for a fixed time interval, usually a month or a year, even though incomes fluctuate with time and respondents may have different perceptions of time in relation to income (Townsend 1979, 426). On the other hand, the respondent may have misunderstood the meaning of 'household' and reports her visiting relative as a household member. Or an adult son or daughter who is rarely home anymore may be 'forgotten' when the respondent is asked to list the members of the household. Nordberg (2004) compared reported equivalised income to administrative records and discovered that in the two lowest income deciles, incomes are over-reported, while in the other eight deciles incomes are underreported, compared to the administrative records. Because of this, the relative financial poverty rate is overestimated in the survey data (ibid.). This interpretation is based of course on the assumption that the administrative record and tax report incomes are closer to the 'true income' and this way more complete and reliable than the reported income in surveys (see Atkinson et al. 1995).

The equation 2-5 refers to cross-sectional measures, where non-systematic measurement errors are assumed to cancel each other out, so that the estimates of X_i are unbiased if random errors are uncorrelated. Hence, it is assumed that for all cases where the error means that the observed value is higher than the true value, there are roughly the same number of cases where the error means that the observed value is lower than the true value. Random errors do not have this convenient attribute when we study the repeated measurements of X_i. In repeated measurements, random errors, rather than nullifying each other's effect, increase observed mobility. If random error in panel data is not corrected, the amount of mobility will be over-estimated (Hagenaars 1992; Chua & Fuller 1987).

Coleman (1968) suggested that if we have panel data from three waves or more we can treat the over-estimation of mobility in panel data by separating the measurement error from true stability. Heise (1969) and Wiley & Wiley (1970) presented a path analytic method for estimating the true stability and the error from test-retest correlations. However, the path analytic, and other structural equation models, based on modelling the covariance or correlation matrix are not suitable for nominal level measurements, in particular because the mean and variance are not independent (Henry 1973). Lazarsfeld and Henry (1968) developed the latent structure model, designed for categorical variables, in the 1950s and 1960s. They defined these models as measurement models that relate a discrete or continuous latent variable to the discrete scores or categories of observed variables with probabilistic relationships. Their work was later developed by Goodman (1974a; 1974b). Van de Pol and de Leeuw (1986) showed how to estimate measurement error in repeated nominal measurements by applying latent structure analysis. They also showed how this can yield a detailed account of the location of the measurement error in each observed variable, rather than a single reliability coefficient.

Rendtel et al. (1998) were the first to use latent structure analysis to treat the over-estimation of poverty mobility in a transition table. Using a latent Markov chain model, originally introduced for this purpose by Langeheine and van de Pol (1990), they arrived at the striking finding that almost half of the observed poverty mobility in their German Socio-Economic Panel data might have been due to measurement error. Later Rendtel et al. (2004) have modelled the combined data of the Finnish ECHP survey and the administrative record incomes with latent Markov models and came out with similar results - mobility in poverty transition tables is over-estimated. Their studies dealt only with Germany and Finland, but similar results could be expected to be obtained in other countries.

2.5.4 Acceptability, practicality and consequences

In addition to the requirement of validity and reliability, some researchers have proposed that poverty measurements should also confront three other criteria. First, poverty measurement should be understandable and approved by the public (Citro & Michael 1995, 38–9). Here, the term public means an entire society, not just the experts who are working on issues relating to poverty. Approved means that poverty measurement should be justified and understood by common sense: poverty measurement should identify those people as poor who are considered as poor in the society in general, and only them. Secondly, the data on which poverty rates are calculated should be available or fairly readily obtained by other researchers, and the technical documentation and epistemological orientations should be clearly brought out (ibid.). This should guarantee the transparency of the data and illustrate what procedures have been carried out before and after the measurement, like sampling, weighting and aggregation.

The third requirement for a good poverty measurement is not a direct concern of the measurement. It is really a social requirement that researchers ought to pay regard to the social consequences that their research might cause (Messick 1989). This requirement is very interesting in the case of poverty measurement, since we are studying a social group that can be seen to be one of the most vulnerable and powerless groups in society. Therefore, the poor, themselves, are very unlikely to take part in the process of describing, defining and estimating poverty: they are generally silent objects of academic and administrative research. Researchers should take this issue into account in their work. Hence, the gathering of information on poverty and the poor always has consequences for the poor, directly through administration or indirectly through discussion and definition.

2.6 Conclusions

Chapter two began by clarifying the difference between the two types of poverty that are distinguished in poverty research; absolute and relative poverty. Poverty in the welfare state is seen to be relative. Relative poverty is defined as the lack of resources to obtain the type of diet, participate in the activities and have the living conditions and amenities that are customary in the society. Absolute poverty, on the other hand, is used to refer to poverty in developing countries, where poverty means famine, a lack of shelter and fatal, epidemic diseases.

Sociological poverty measurement mainly uses head-count poverty measures that only identify the poor and tell the prevalence of poverty in the population. Conditional probabilities and other estimates of association are then used to find explanatory factors such as the causes of poverty. In economics, simple head-count poverty measures are usually used only as a component of poverty indexes that also measure other attributes of poverty, for example, the depth of poverty. Aggregated poverty indexes naturally give more detailed information about poverty compared to simple head-count measures, but this is gained at the cost of comprehensibility. Also, the most crucial error of measurement in poverty indexes is derived from the head-count component of the index. Partly because of this, the most influential poverty measurements in social policy are all head-count measures.

In most of the cases studied, the household is taken as the economic unit that is assumed to pool the resources, amenities and needs. Usually a head-count poverty measure measures either the lack of resources or the poor living conditions of the household or the opinion of the head of household. Poverty indicators which use low incomes or other material resources as the indication of poverty are called indirect measures. Indicators measuring poor living conditions are called direct measures. Indicators based on subjective questions are called subjective measures. The poverty threshold can be set in the distribution of resources, deprivation or subjective views either using some external criteria, like what are seen as basic commodities by the experts, or using some function of a distribution, for example 60 per cent of median income. The threshold can also be set using multiple criteria, for example, the point in the distribution of income after which deprivation starts to rise rapidly.

However, all the head-count poverty measures are hampered by difficulties in actually measuring low incomes, poor living conditions or a subjective view of deprivation. One consequence of this is that different people and families are identified as poor by different measures. Because of this, some researchers have suggested that we should treat different measures as alternative ways to gain information on the same complex phenomenon. In this multidimensional approach, poverty is measured with direct, indirect and subjective indicators side-by-side. Each measure gives complementary information on different aspects, or dimensions, of poverty.

Also in recent years more and more European poverty researchers have started to point out that poverty is a temporal phenomenon and so it should be measured longitudinally. Taking the temporal aspect into consideration is essential both to understand poverty and for the development of a social policy. In the United States, longitudinal poverty research is well developed. However, in the European Union longitudinal poverty studies have only in the recent years become more numerous. This is mainly due to the new European Union level panel study, the European Community Household Panel (ECHP).

Chapter two ends with the important, but often ignored, issues of measurement validity and reliability. The concept of validity is used to describe whether the interpretations made from the measurement are reasonable. Traditionally, reliability and validity have been seen as two different, but related, things. The validity of the measurement is judged rhetorically outside the actual measurement situation and the error of measurement, reflected by reliability, is seen as a problem concerning the measurement device. It is emphasised how important it is to separate the measurement and structural components in a model, especially when modelling panel data where, if ignored, the random measurement error results in mobility being over-estimated.

In this chapter we have presented the definition(s) of poverty and how it is operationalised within a head-count poverty measure. Now it is time to start on empirical analyses. We will begin by presenting the data, methods and the research hypotheses of this study.

3 Data, methods and research hypotheses

3.1 Introduction

Based on previous empirical studies, we have a good basis of supposition as to what the poverty dynamics might be in the ten countries we are about to study. There are also some interesting theories, which have been presented in contemporary poverty and social mobility research that we can use as our starting point when modelling the structure of poverty transitions. For example, the so-called individualisation thesis argues that poverty is, or better has become, mostly short duration incidences and is now connected more to the phase of life-course than to the structure of social stratification (Leisering & Leibfried 1999). Some other hypotheses for testing can be derived from the welfare state coverage in the country (Fritzell 1990), from the constant (core) fluidity thesis in social mobility studies (Erikson & Goldthorpe 1992, 24–26), from the classical test theory and from the fact that observed mobility is over-estimated in panel data due to random error (Hagenaars 1992).

From these theories and theses four formal testable research hypotheses will be derived. The first hypothesis will state that the population is heterogeneous according the transition of poverty. The second research hypothesis will state that observed mobility is higher than true mobility due to the random error. The third hypothesis will test the assumption that poverty dynamics behind different head-count poverty measures are common and the fourth that the dynamics are common across countries.

The chapter is structured in the following way: after presenting the research hypotheses in section two, the data and variables is presented in section three. Section four presents the descriptive poverty (dynamics) figures using the selected three poverty classifications. The fifth section introduces the log-linear model and its latent variable extension, the latent class model, which are the main methods of analyses in this study. The chapter ends with concluding remarks.

3.2 Research questions

There are several theoretical backgrounds from which the tested research hypotheses are derived. The first theory, or thesis, is the so-called individualisation thesis, originally formulated by Ulrich Beck (1994, 19) and later applied to the theories of poverty by Leisering and Leibfried (1999). The individualisation thesis argues that contemporary poverty has become 'transitory', 'biographised' and 'transcendent' over social boundaries contrast to the past class-based, often life-long poverty that was seen in the early industrial societies. The thesis argues that poverty in affluent welfare states touches also the middle classes at the same time when poverty has become a relatively transient phenomenon in people's lives and it is more associated with particular events in the life-course (ibid., 9). Leisering and Leibfried (1999, 239) gave perhaps the best know presentation of the individualisation thesis in poverty research:

> 'Poverty is no longer (if it ever was) a fixed condition or a personal or 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 democratisation (or transcendence) of poverty.'

The above statement indicates that the incidence of poverty is somewhat random across time and that more or less the entire population is (in theory) exposed to poverty. A model that would describe this kind of society would assume that no one is permanently in or outside poverty. On the contrary, the whole population is expected to experience poverty at some point in their life. However, if we can show that the population can be divided into groups in such a way that a part of the population is predetermined into poverty, while other parts never or hardly ever experience poverty, this would support the so-called cumulative disadvantage hypothesis that is, in a way, a counterhypothesis for the individualisation thesis. The cumulative disadvantage thesis argues that certain parts of the population are predetermined to have a high risk of being in poverty. According to Layte and Whelan (2002) the risk of poverty is (still) tightly connected to the social class structure. The closer the population is to the always/never in poverty -dichotomy, the stronger the evidence we get for the cumulative disadvantage thesis. The larger the 'intermediate' group(s) of movers is (are) between these two extreme categories of always or never being in poverty, the stronger the evidence we get for the individualisation thesis. So we hypothesise that the population contains at least three groups that have different poverty trajectories and to test this we formulate our first research hypothesis as;

Hypothesis #1: The population is heterogeneous in their relation to poverty dynamics.

The second research hypothesis is based on the classical test theory. According to the classical test theory, non-systematic measurement errors cancel out with cross-sectional measures. Therefore, it is assumed that for all non-poor cases which are misclassified as poor, there are roughly the same number of cases of the poor being misclassified as non-poor. But random errors do not have this convenient attribute when we study the dynamics of the phenomenon. Here random errors, rather than nullifying each other's effect, increase observed mobility. If the random error in the transition table is not corrected, the amount of mobility will be over-estimated, as proposed by Hagenaars (1992), for example. So, we can assume that a part of the observed poverty mobility is caused by the random error, as has been reported in the few previous studies on the topic (Rendtel et al. 1998; Breen & Moisio 2004). The second research hypothesis is then formulated as;

Hypothesis #2: Both absolute and relative (fluidity) poverty mobility are over-estimated because of random error

The third research hypothesis is derived from the thesis proposed by David Gordon (2002) that different poverty indicators measure different phases of the same dynamic process. According to him, it takes a certain time before the lack of resources develops into deprivation. For example, a sharp drop in income can mean entry into poverty according to a financial poverty measure, but a poverty measure that measures living conditions will still show that the person (or household) is not suffering from deprivation. In time, the lack of resources will materialise into poor living conditions, but before this, there is a mismatch between the indirect resource based poverty measure and the direct living conditions based deprivation measure. When the income then rises, it will takes some time before the living conditions improve and there is a mismatch again between the direct and indirect measures. Since poverty spells are relatively short in duration, the aggregate of these mismatches causes serious problems in identifying the poor. So if Gordon's thesis is correct, we should be able to find a common relative mobility, i.e. fluidity patterns at least behind the two objective poverty indicators - financial poverty and housing deprivation. It is difficult to predict what the dynamics of subjective deprivation might be, but we could expect that they follow to a great degree the dynamics of the objective measures. Therefore, the third research hypothesis is formulated as;

Hypothesis #3: The pattern of poverty fluidity is common between poverty classifications.

The fourth research hypothesis is derived from theories that suggest either differences or similarities in poverty dynamics across countries. Fritzell (1990) made a hypothesis that the extensive welfare state has reduced poverty mobility by reducing the impact of sudden and unpredicted market events. The welfare state is a wide set of welfare arrangements aiming to protect individuals and families against social risks. We might hypothesise that the more extensive and universal this coverage is, the more it reduces poverty mobility. In our data we have countries which have very different welfare states, so if Fritzell's thesis is correct, we should see differences in poverty dynamics between these countries. We might also assume that in the countries with a more equal income distribution the poverty risk is more equally distributed, meaning that a larger proportion of the population is experiencing poverty incidences and the poverty mobility is higher. Additionally, in the countries with a more equal income distribution, the average distance from the poverty threshold is smaller than in the highly unequal distribution, making the crossing of the poverty threshold again more likely across population. So we might expect that income equality increases poverty mobility (Breen & Moisio 2004). The countries under investigation here show large differences in income inequality, so if it is the case that income equality increases poverty mobility, we should again see differences in the dynamics between the countries. The flexibility of the labour market can be also an important factor in determining how easy it is to move across the poverty threshold. It can be hypothesised that inflexibility in the labour markets decreases poverty mobility and flexibility increases poverty mobility (ibid.). Again, the studied countries show differences in how flexible their labour markets are, so we should be able to observe differences in poverty dynamics if this assumption is valid.

However, there are theories that lead us to expect that the dynamics of poverty are somewhat similar across countries. For example, the core social fluidity patterns are remarkably similar across countries and time. This can be seen as the constant flux in the patterns of fluidity in industrialized societies that have a similar type of market economy and a similar family system (Erikson & Goldthorpe 1992). The hypothesis about a common structure of poverty dynamics is also supported by recent studies, where poverty fluidity is shown to have remarkably similar patterns in the EU countries, despite the large differences in national poverty rates (Whelan et al. 2000; Layte & Whelan 2003). So we formulate the fourth research hypothesis as;

Hypothesis #4: Poverty fluidity is common across countries.

The direct, indirect and subjective measures of poverty and deprivation and their four repeated measurements in the ten countries are used to test these hypotheses. The variables and the data are presented in the next section.

3.3 Data and variables

Often the data limits what can be empirically studied. This is especially true with a topic that requires a longitudinal research setting. To execute longitudinal household surveys requires a lot of money and a continuing (and for this well-financed) research community to repeat the surveys over a long time-span. Longitudinal poverty research has been strong in the United States since the 1980s, but Europe is only now catching up. The European Community Household Panel (ECHP) between 1994-2001 will, and already has, instigated longitudinal poverty research in Europe. Undoubtedly the 'successor' of the ECHP panel, the EU-SILC panel will carry on the longitudinal poverty research in the EU. (see Atkinson 2002.)

The data used in the analysis is from the European Community Household Panel (ECHP). The ECHP household panel surveys are carried out by national statistical offices or national research institutes. Eurostat is responsible for gathering and standardising the data for comparative use (see Epunet 2003). The ECHP is based on annual household surveys that were conducted between 1994–2001. It attempted to interview all adult members of the household (aged 16 and over by the end of the survey reference year) and individual level information was gathered on income, social transfers, employment, education, health and social relationships. The demographic information of the children in the household were also taken. Household level information was gathered from the head of household about the financial situation and living conditions of the family. Country-level information was provided about population, exchange rates and purchasing power parities. All sample persons, i.e. those adults and children included in the sample of the first wave, were followed up. If a sample person moved to a new household, this household was followed up and all its non-sample adults were interviewed. (Eurostat 1994.)

Twelve EU countries started the panel in 1994 and Austria and Finland joined the panel two years later. Sweden is the only EU-15 country that is not in the panel, although, it provided cross-sectional household surveys for the use of the ECHP. In the winter of 2002–2003 five annual waves between 1994–1998 were prepared for research purposes. All eight waves are expected to be released by 2004. Since the information on incomes in the ECHP refers to the previous years incomes, it was only possible to use four waves, i.e. waves 1994–1997, in the analysis, because we need information both from the current incomes and the current household's structure to be able to calculate the income per consumption unit. Eleven countries had the waves 1994–1997 in the ECHP and, from them, we had to drop Germany's panel, because it did not have the housing condition information we needed for the analysis. Altogether, we have four annual waves from ten EU countries for the analysis of poverty dynamics.

Data quality with respect of unit non-response and attrition rates is exceptionally good in most of the countries. The response rate in the first wave are 84% in Belgium, 62% in Denmark, 80% in France, 90% in Greece, 56% in Ireland, 91% in Italy, 86% in the Netherlands, 89% in Portugal, 76% in Spain and 72% in the UK (Eurostat 1997). In this thesis balanced panels are used, which means that cases that are not observed in all four waves were excluded. The proportion of individuals observed in all four waves from those observed in the first wave is 77% in Belgium, 66% in Denmark, 74% in France, 75% in Greece, 62% in Ireland, 81% in Italy, 79% in the Netherlands, 84% in Portugal, 70% in Spain and 83% in the UK (Watson 2002). Data is weighted by the base weight variable, as Eurostat recommends (see Peracchi 2002, 83–4).

Three established and well-known measures of poverty and deprivation were selected for the analysis: the relative financial poverty threshold, the housing deprivation scale and the economic strain scale (see Table 3.3.1). The financial poverty threshold is measuring low material resources and the housing deprivation scale can be viewed as measuring objective life-style deprivation. Townsend (1979, 418–21) considered questions that asked about the subjective feeling of economic strain and deprivation, as a way of measuring of subjective deprivation. We will follow this separation between the objective and subjective deprivation measures.

Adequate material resources are a necessary condition for material well-being and the level of disposable income is probably the most widely used indicator for measuring material resources. Here we use the relative financial poverty threshold, where the poverty threshold is set to be 60% of median equivalent incomes. The equivalisation scale is the modified OECD scale (see 2.3.2). Those households having an equivalent income below this threshold are classified as income poor. The relative financial poverty threshold is one of the EU structural indicators and usually referred to as the 'official' EU poverty threshold. For a more detailed description on the relative financial poverty measure, see Atkinson et al. (2002, 78–109).

Indirect (income) poverty measures have been criticised on the basis that resources equate with well-being very differently depending on the personal abilities and needs, social contacts, the place of residence and the access to public services. Direct measures that measure life-style deprivation, on the other hand, are seen to reflect the actual materialisation of resources. This way, a direct measure can shed light on poverty from another angle than an indirect measure, giving, if not better then at least complementary, information about poverty. The direct poverty measure used here is a housing deprivation indicator. The indicator is a short version of Eurostat's nine item scale of multiple problems in accommodation. The questions are asked of the head of household (Eurostat 1998). The questions are based on the (implicit) assumption that households wish to avoid these problems in accommodation. The scale is dichotomised into a head-count measure so that it is

TABLE 3.3.1: Description of the poverty and deprivation classifications

Name of the variable and explanation	Coding
Relative financial poverty measure	
Equivalised net income (modified OECD scale adjusted) below the poverty threshold that is set at 60% of the national median equivalised net income.	Over 60% => 1 Below 60% => 2
Subjective deprivation	
Is the household able to make ends meet? (1) With great difficulty, (2) with difficulty, (3) with some difficulty, (4) fairly easily, (5) easily and (6) very easily.	3,4,5 or 6 => 1 1 or 2 => 2
Housing deprivation	
Accommodation have shortage of (1) space, (2) leaky roof, (3) damp walls, (4) rot in window frames or floors or (5) inadequate heating facilities.	0 or 1 => 1 2 or more => 2

easier to compare, both substantially as well as technically, its rates and dynamics with those of the financial poverty measure.

The subjective view of deprivation, or economic strain, supplements the picture of poverty that (objective) direct and indirect poverty indicators give. With a subjective deprivation measure, we have to rely on that respondents having at least to some degree a shared understanding of what the minimum living standards are that should be 'met'. Perhaps it is the famous 'to be able to appear in the public without shame', but for different people this might mean different things. The subjective indicator used here is based on the question asked to the head of household 'is your household able to make ends meet?' The classification is done by assigning those reported 'difficulties' or 'great difficulties' into the subjective deprived class and others to the non-deprived class. The scale is dichotomised again so that comparisons with the financial poverty and objective deprivation measures would be easier both substantially and technically. The technical documentation of the three head-count poverty indicators is presented in the table 3.3.1.

Four repeated measurements with a dichotomous variable, results in a transition table of 16 cells. Each of the three poverty classifications have their own 16 cell transition table that are presented in the Tables 3.3.2–3.3.4. In table 3.3.2 the transition table of financial poverty in each country is presented, in table 3.3.3 the transition table of the housing deprivation and in table 3.3.4 the transition table of subjective deprivation is presented. The poverty and deprivation status of the person in each annual wave is presented in the four left-hand columns. The class of poor/deprived has the value 2, the class of non-poor/deprived correspondently the value 1. The cell frequencies for each country are presented in the columns and in the last row there are the total sample sizes for each country. The report from item nonresponse is presented in the Appendix B. The proportion of missing values is quite modest in the first wave, but the proportion of cases excluded because of the missing value in one or more waves is higher (see Appendix B). However, usually less than five percent of the cases are excluded due to the missing value, so the overall item nonresponse does not question the reliability of data. The only panel where item nonresponse is a problem is the housing deprivation panel of the UK: 25.9% of the cases have missing value in the first wave and 32.8% of cases is eventually excluded due to one or more missing value. This cast a serious doubt over the deprivation panel of UK. We will keep this panel in the analysis, but the high nonresponse should be kept in mind when results are interpreted.

TABLE 3.3.2: Financial poverty transition tables

1994	1995	1996	1997	DK	NL	B	F	IRL	I	EL	E	Pl	UK
1	1	1	1	3 761	7 264	4 626	9 667	5 695	10 840	6 588	9 263	7 457	6 422
1	1	1	2	364	290	246	480	377	520	441	621	381	523
1	1	2	1	78	137	115	282	198	511	337	483	403	228
1	1	2	2	65	120	104	141	204	262	242	287	154	236
1	2	1	1	93	229	174	239	232	498	303	456	218	201
1	2	1	2	17	78	91	83	71	144	39	176	53	66
1	2	2	1	9	123	58	124	84	172	165	254	96	157
1	2	2	2	23	128	93	163	208	270	293	310	183	311
2	1	1	1	133	302	232	377	275	683	373	525	479	412
2	1	1	2	30	30	50	129	45	162	103	528	84	123
2	1	2	1	43	46	39	60	157	114	111	226	150	103
2	1	2	2	35	47	38	114	52	180	180	263	133	91
2	2	1	1	38	118	91	222	174	335	201	300	282	203
2	2	1	2	25	57	73	114	71	240	89	159	142	78
2	2	2	1	29	105	201	208	199	268	301	199	249	278
2	2	2	2	98	334	480	1086	539	1 053	936	679	1 287	880
			Total	4 841	9 408	6 711	13 489	8 581	16 252	10 702	14 729	11 751	10 312

TABLE 3.3.3: Housing deprivation transition tables

1994	1995	1996	1997	DK	NL	B	F	IRL	I	EL	E	Pl	UK
1	1	1	1	4 477	8 322	5 300	9 769	6 894	13 336	6 448	10 710	4 964	5 135
1	1	1	2	125	195	155	487	216	422	492	655	347	133
1	1	2	1	132	193	148	284	174	461	368	584	283	91
1	1	2	2	12	104	45	183	135	164	216	231	439	48
1	2	1	1	117	307	247	484	217	484	448	509	285	150
1	2	1	2	6	50	179	88	21	106	123	184	82	25
1	2	2	1	56	55	55	239	43	130	134	201	167	72
1	2	2	2	30	141	50	136	113	211	385	572	601	59
2	1	1	1	218	366	357	875	482	1009	1364	960	716	619
2	1	1	2	10	55	71	148	28	123	174	288	146	45
2	1	2	1	112	48	31	131	65	179	211	272	88	52
2	1	2	2	42	55	32	239	194	124	256	248	293	44
2	2	1	1	61	134	224	394	126	351	422	353	549	112
2	2	1	2	19	51	30	214	34	101	219	222	368	23
2	2	2	1	36	108	133	315	111	256	344	279	458	85
2	2	2	2	44	176	195	603	228	682	1122	632	2921	128
			Total	5 497	10 360	7 252	14 589	9 081	18 139	12 726	16 900	12 707	6 821

TABLE 3.3.4: Subjective deprivation transition tables

1994	1995	1996	1997	DK	NL	B	F	IRL	I	EL	E	Pl	UK
1	1	1	1	4 043	7 768	5 133	9 145	4 680	10 930	2 525	6 171	4 509	7 959
1	1	1	2	169	272	260	568	360	842	532	702	645	230
1	1	2	1	181	256	204	598	381	646	288	745	343	227
1	1	2	2	49	119	93	271	197	332	577	505	449	111
1	2	1	1	81	234	210	491	349	741	472	653	508	357
1	2	1	2	34	59	61	198	63	245	205	338	167	80
1	2	2	1	45	131	106	324	175	263	289	1020	307	106
1	2	2	2	50	131	102	303	212	406	822	566	727	104
2	1	1	1	389	388	216	723	605	987	801	1003	947	469
2	1	1	2	57	101	35	193	238	243	318	376	160	69
2	1	2	1	31	84	53	190	192	187	247	396	209	74
2	1	2	2	28	111	77	218	261	205	653	658	321	52
2	2	1	1	87	107	206	325	247	561	389	552	337	171
2	2	1	2	9	83	47	251	154	350	368	634	406	75
2	2	2	1	69	162	66	263	438	462	508	662	298	134
2	2	2	2	217	378	309	624	879	995	3714	1 979	2 379	211
			Total	5 539	10 384	7 178	14 685	9 431	18 395	12 708	16 960	12 712	10 429

3.4 Descriptive poverty figures

It is difficult to conceive the transition of poverty taking place in Tables 3.3.2, 3.3.3 and 3.3.4 solely by observing the absolute cell frequencies. Some basic descriptive figures are needed so that we can have a comprehension of the dynamics we will model in the following chapters. So, in Tables 3.4.1, 3.4.2 and 3.4.3 some descriptive estimates for the longitudinal financial poverty, housing deprivation and subjective deprivation are presented. The first four columns present the poverty rates in each wave, showing that the three indicators estimate different proportions of the population as poor or deprived. The highest proportion is given by the subjective deprivation measure, circa 27 per cent, while the financial poverty and housing deprivation measures estimate around 18 per cent to be either poor or deprived. The next five columns show the percentage of the population according to the number of poverty or deprivation incidences they have experienced over the four years. The last three columns on the right hand side present what the poverty or deprivation risk is in the second, third and fourth wave if the person has been regarded as poor or deprived in the first wave.

There do not seem to be any major increases or decreases in the financial poverty rate in any country during the four-year follow up period, except in Portugal where the poverty rate has decreased. Also, in Denmark, the financial poverty rate jumps up almost five per centage points between 1996 and 1997. An increase this large indicates that there is a systematic measurement error in the balanced panel for Denmark, especially since a similar increase in poverty rates in Denmark has not been reported elsewhere. Otherwise, financial poverty rates vary between ten (Denmark and the Netherlands) and 22 per cent (Spain, Portugal and the UK). The unweighted mean across all the countries is 18 per cent and this is almost entirely consistent for all four waves.

TABLE 3.4.1: Descriptive figures for financial poverty dynamics

Country	Poverty rates (%) in each wave				Proportion classed as poor *i* times out four measurement times					Risk that poverty recurs after 1, 2 or 3 years		
	wave 1	wave 2	wave 3	wave 4	0 out 4	1 out 4	2 out 4	3 out 4	4 out 4	P(1|2)	P(1|3)	P(1|4)
Denmark	8.9	6.9	7.9	13.6	77.7	22.3	8.5	4.4	2.0	.44	.48	.44
Netherlands	11.0	12.4	11.0	11.5	77.2	22.8	12.6	7.1	3.6	.59	.51	.45
Belgium	18.0	18.8	16.8	17.5	68.9	31.1	19.6	13.2	7.2	.70	.63	.53
France	17.1	16.6	16.2	17.1	71.7	28.3	18.1	12.5	8.1	.71	.64	.62
Ireland	17.6	18.4	19.1	18.2	66.4	33.6	21.0	12.5	6.3	.65	.63	.47
Italy	18.7	18.3	17.4	17.4	66.7	33.3	19.7	12.4	6.5	.62	.53	.54
Greece	21.4	21.7	24.0	21.7	61.6	38.4	24.9	16.8	8.7	.67	.67	.57
Spain	19.5	17.2	18.3	20.5	62.9	37.1	22.9	10.9	4.6	.46	.47	.57
Portugal	23.9	21.4	22.6	20.6	63.5	36.5	23.9	17.0	11.0	.70	.65	.59
UK	21.0	21.1	22.1	22.4	62.3	37.7	24.5	15.9	8.5	.66	.62	.54
Total	18.4	17.9	18.2	18.4	67.0	33.0	20.4	12.7	6.9	.63	.59	.55

TABLE 3.4.2: Descriptive figures for housing deprivation dynamics

Country	Deprivation rates (%) in each wave				Proportion classed as deprived *i* times out four measurement times					Risk that deprivation recurs after 1, 2 or 3 years		
	wave 1	wave 2	wave 3	wave 4	0 out 4	1 out 4	2 out 4	3 out 4	4 out 4	P(1|2)	P(1|3)	P(1|4)
Denmark	9.9	6.7	8.4	5.3	81.4	18.6	7.8	3.1	0.8	.30	.43	.21
Netherlands	9.6	9.9	8.5	8.0	80.3	19.7	9.4	5.1	1.7	.47	.39	.34
Belgium	14.8	15.4	9.5	10.4	73.1	26.9	14.4	6.1	2.7	.54	.36	.31
France	20.0	17.0	14.6	14.4	67.0	33.0	18.4	10.3	4.1	.52	.44	.41
Ireland	14.0	9.8	11.7	10.7	75.9	24.1	12.1	7.5	2.5	.39	.47	.38
Italy	15.6	12.8	12.2	10.7	73.5	26.5	13.4	7.6	3.8	.49	.44	.36
Greece	32.3	25.1	23.9	23.5	50.7	49.3	28.3	18.3	8.8	.51	.47	.43
Spain	19.3	17.5	17.9	18.0	63.4	36.6	20.6	11.6	3.7	.46	.44	.43
Portugal	43.6	42.7	41.3	40.9	39.1	60.9	48.1	36.5	23.0	.78	.68	.67
UK	16.3	9.6	8.5	7.4	75.3	24.7	10.2	5.0	1.9	.31	.28	.22
Total	20.7	18.3	17.0	16.3	66.3	33.7	20.2	12.3	6.0	.58	.49	.45

TABLE 3.4.3: Descriptive figures for subjective deprivation dynamics

Country	Deprivation rates (%) in each wave				Proportion classed as deprived *i* times out four measurement times					Risk that deprivation recurs after 1, 2 or 3 years		
	wave 1	wave 2	wave 3	wave 4	0 out 4	1 out 4	2 out 4	3 out 4	4 out 4	P(1|2)	P(1|3)	P(1|4)
Denmark	16.0	10.7	12.1	11.1	73.0	27.0	12.2	6.7	3.9	.43	.39	.35
Netherlands	13.6	12.4	13.2	12.1	74.8	25.2	14.1	8.3	3.6	.52	.52	.48
Belgium	14.0	15.4	14.1	13.7	71.5	28.5	16.1	8.4	4.3	.62	.50	.46
France	19.0	18.9	19.0	17.9	62.3	37.7	21.5	11.3	4.2	.52	.46	.46
Ireland	32.0	26.7	29.0	25.1	49.6	50.4	32.4	20.6	9.3	.57	.59	.51
Italy	21.7	21.9	19.0	19.7	59.4	40.6	23.1	13.1	5.4	.59	.46	.45
Greece	55.1	53.3	55.9	56.6	19.9	80.1	63.7	47.7	29.2	.71	.73	.72
Spain	36.9	37.8	38.5	33.9	36.4	63.6	45.3	26.5	11.7	.61	.59	.58
Portugal	39.8	40.3	39.6	41.3	35.5	64.5	45.3	32.5	18.7	.68	.63	.65
UK	12.0	11.9	9.8	8.9	76.3	23.7	11.4	5.5	2.0	.47	.38	.32
Total	27.6	26.9	26.8	25.8	53.1	46.9	30.8	19.5	9.9	.62	.58	.56

The proportion of the population who have experienced financial poverty during the four years is around twice the size of the poverty rate. For example, in the Netherlands the poverty rate is 11 per cent and the proportion of the population that has experienced poverty at least once during the four years is 23 per cent. This ‘double-ratio’ between the poverty rate of the country and the proportion of population that has experienced poverty at least once during the four years seems to hold good for every country. When observing the proportion of the population who have experienced poverty twice, three or four times during the four years, we can see that the proportion decreases sharply when the number of poverty incidences increase. In Denmark, for example, only two per cent of the population has experienced uninterrupted financial poverty over all four years. The proportion of population that experienced uninterrupted poverty is higher in other countries, but it seems to be that, in every country, the per centage of the population in a long-term and interrupted poverty spell is always much smaller than the cross-sectional poverty rate.

If financial poverty spells seem to be mainly short-duration incidences, the risk of poverty reoccuring seems to be very persistent. When observing the risks P(i|1) to be in financial poverty again after a year (i=2), two years (i=3)or three years (i=4), we can see that the risk does not decrease. Even in Denmark, where long financial poverty spells are very rare, we can see that the incidence of financial poverty increases the risk for financial poverty in the next year to .44. This increased financial poverty risk does not decrease even after three years. The risk P(i|1) that financial poverty will reoccur is higher in other countries, but the pattern is the same. An incidence of financial poverty seems to cast a long shadow, as the risk of financial poverty is high even years later.

As opposed to the financial poverty rates, we can detect a fragile but clear decreasing trend in the housing deprivation rates from 1994 to 1997. There is also clearly a bigger variance between countries in their housing deprivation rates than there is with financial poverty rates. The housing deprivation rate varies from nine per cent in Denmark and in the Netherlands to 40 per cent in Portugal. There is also big variance between the proportion of population who experienced housing deprivation at least once during the four years that were studied. The highest and the lowest proportions can again be found in Denmark, 22 per cent, and in Portugal, 61 per cent. The double-ratio rule also seems to hold good between the housing deprivation rate and the proportion of population experienced housing deprivation at least once during the four years. The proportion of the population who have experienced housing deprivation at least once in four years is around double what the cross-sectional deprivation rate is. But the proportion drops sharply when the number of incidences increases, with the exception of Portugal. The proportion of the population who have been in housing deprivation uninterruptedly for four years is only a fraction of the annual deprivation rate in every country.

The risk of deprivation reoccuring P(i|1) seems to be slightly lower than was seen with the financial poverty, but the pattern is the same. Even a single incidence of housing deprivation increases the risk that the deprivation will reoccur after a year, two or three years later and this increased risk does not decrease. For example in the Netherlands, the incidence of housing deprivation in 1994 increases the risk of reoccurrence of housing deprivation to .47 in 1995, to .39 in 1996 and to .34 in 1997. The average risk in the Netherlands for housing deprivation is .09.

There also seems to be a slight decrease in subjective deprivation rates between 1994 and 1997 in most of the observed countries. The variance in the subjective deprivation rate is large between the countries, as it was with the housing deprivation rate. The subjective deprivation rates vary from 10 per cent in the UK to 55 per cent in Greece. Again, the proportion of the population that has experienced subjective deprivation at least once over the four years is about double the proportion identified as subjectively deprived cross-sectionally. With the exception of Portugal, Spain and Greece, the proportion of the population that has suffered uninterrupted subjective deprivation through all four years is only a fraction of the cross-sectional subjective deprivation rate. For example, in the UK the subjective deprivation rate is around 10 per cent, depending on the year of measurement, but the proportion of the population living in a household whose head reports difficulties to make ends meet for all four years is only 2 per cent.

But again, if there has been an incidence of subjective deprivation, this will increase the risk of subjective deprivation re-occurring in the near future. For example in the UK, reporting subjective deprivation in 1994 increases the risk of subjective deprivation to .47 in 1995, to .38 in 1996 and to .32 in 1997. The average risk in the UK of subjective deprivation is around .10. So the transition of subjective deprivation repeats the pattern observed in the financial poverty and the housing deprivation transition tables.

We can now sketch a rough picture of the structure of poverty and deprivation dynamics that underlie the three transition tables. The poverty and deprivation dynamics seem to have the following characteristics: (1) long and uninterrupted poverty or deprivation spells are not common and (2) even a single poverty (or deprivation) incidence predicts that poverty (or deprivation) will reoccur in the near future. A model describing these characteristics would be a model where the majority of population never experience poverty and a small group of people live in constant poverty. Between these two groups there is a movers group, consisting of 20–40 per cent of the population, who move in and out of poverty and who live in with the constant high risk of poverty. This preliminary picture of poverty and deprivation dynamics is congruent with the hypotheses we derived from the theory and previous empirical studies in 3.2. However, to be able to test is this model of poverty dynamics correct, we need to utilise log-linear modelling.

3.5 Methods

3.5.1 Modelling stochastic processes in discrete time and space

The terms 'stochastic' and 'random' do not refer to the same thing, although it is quite a common misunderstanding to assume that they do. A random process is an unpredictable process, lacking all systematic behaviour. But if we can describe the process with some probabilities, we observe a stochastic process. When poverty incidences are measured longitudinally, using repeated classifications, we observe a stochastic process, since few would argue that the incidences of poverty are purely random. Being poor at given moment is a quite good predictor that the person will also be poor in time t+1. And correspondingly, if we know that a person has never been poor, it is reasonable to predict that the person will not be poor in the (near) future. So, it is safe to say that the transition of poverty, or poverty dynamics, is a stochastic, not a random, process.

Next, we will present techniques for modelling the stochastic process observed in poverty and deprivation transitions tables. Preliminary analyses in the previous section (and previous empirical studies) imply that different countries having different levels and distributions of poverty might have a similar pattern of poverty dynamics. Also, we might expect that there is only a small group of people stuck in permanent poverty and that there is high mobility in and out of poverty from one year to the next. Luckily, we do not have to start to convert these assumptions into testable models from scratch. The underlying structure of the stochastic process has long interested statisticians and other scholars. As a result of this work, there is an established family of models that can be used to test various hypotheses about the underlying structure of a stochastic process.

Markov chain models are widely used for modelling stochastic processes which have been observed in categorical panel data. Markov models are built around the 'simple' first-order single Markov chain. The first-order Markovian process, or simple Markov chain model, assumes that the state occupied at time t depends only on the state occupied at time $t-1$. So the model assumes that there is independence between the states occupied at time t and previous time points $t-j$ when $j>1$, conditional on the state occupied at time $t-1$. In other words, the state occupied at time $t-2$, or earlier, has no effect on the situation in time t, once the state occupied at time $t-1$ is taken into account. The second order Markov chain would allow both the states occupied at time $t-1$ and $t-2$ to have an effect on the state occupied at time t. However, higher order Markov chain models are not very popular in the empirical analyses, simply because that they do little to simplify the modelled stochastic process – and simplifying the associations in the data is the aim of all modelling. Also, higher order Markov chains are quite difficult to interpret and give a verbal expression of.

One problem with the simple Markov chain model, however, is that it rarely fits the data. There are two reasons for this (Langeheine & van de Pol 1990). First, the simple Markov chain model assumes a homogeneous population. This problem can be circumvent by increasing the number of Markov chains in the model and this way allow heterogeneity in the population. Markov models with multiple chains are often referred to as mixed Markov models. The second reason is that the model does not allow for measurement error. This problem can be tackled by constructing a measurement model that describes the relationships between the observed and true values. The 'two chains Markov model' tests the hypothesis that there are in fact two simple Markov chains behind the stochastic process. Or put in other words, the population contains two groups which each follow their own Markovian chain. Maybe the best-known Mixed Markov model is the Mover-Stayer model, where the transition probabilities in the second chain are restricted to be either 1.0 or 0.0. Hence, the second chain describes the non-movers, i.e. stayers, in the population. The first chain in a Mover-Stayer model then follows the first order Markov process, describing the transition probabilities of the movers. In our poverty transition tables, this would describe a model where there are two underlying processes in the transition table: a chain containing those who almost certainly will not move between succeeding years and a second chain containing people who move in and out of poverty according to the first order Markovian process. The Mover-Stayer model would then give estimates showing the fraction of the population who are movers and the fraction of the population who are stayers and what the transition probabilities (fluidity) are in the movers' chain.

The second way to improve the goodness of fit of a Markov model, i.e. separating the true values from the observed ones, can be done by combining Latent Class and Markov chain modelling. Coleman (1968) showed that we can estimate measurement error in repeated measurements if we have panel data from three or more waves, as was discussed in 2.5.3.

Van de Pol and de Leeuw (1986) showed how to estimate measurement error in repeated nominal measurements by applying Latent Markov models. The Latent Markov model yields the estimates for the relationships between the true and the observed values and a detailed account of the location of the measurement error. The Latent Markov model is a member of the large family of latent structure models. Lazarsfeld and Henry (1968) were the original developers of the latent structure models and they defined them as measurement models that relate, in a probabilistic way, a discrete or continuous latent variable to the discrete scores or categories of manifest variables (see 2.5.3).

The most popular technique for building simple, Mixed and Latent Markov models for empirical testing is log-linear modelling, which can be easily expanded to (latent class) models containing one or more latent variable(s). In the next section we will present the basic principles of this flexible modelling technique.

3.5.2 Log-linear modelling

A transition table is a special type of frequency table. Because variables in a transition table are repeated classifications across time *t*, there is a certain causal structure in the table that has to be taken into account when interpreting and modelling it. However, since a transition table is a frequency table, we can use the same modelling techniques that we use when modelling frequency tables. Log-linear modelling, with certain parameter restrictions, gives us a powerful tool for modelling any stochastic process we believe is underlying in a transition table. The aim of log-linear modelling is to simplify and reveal the basic structure of this underlying stochastic process in the transition table. Unfortunately there is usually a trade-off between the model parsimony and the model fitness and there is no rule of thumb when the model has adequate fit or parsimony. Because of this, constructing and fitting a log-linear model is open to a various interpretations, so this work should be always be guided by theory and empirical knowledge (Pöntinen 1981).

In practice, parametric analysis methods for categorical variables are all based on the same idea as the chi-squared (χ^2) -test for a two-dimensional frequency table. Although dimensions in the frequency table may be increased and an additional latent variable may be included in the model, the basic idea of the χ^2 -test still remains: the observed frequency table (or cell probabilities) is (are) compared to the estimated table generated by a particular model. When moving to log-linear models and latent class models, the 'observed' frequencies and probabilities in every cell are reproduced by log-linear functions or by conditional probabilities. However, this does not change the fundamental idea of fitting an estimated model to the observed frequency table.

The chi-squared test value for a two-dimensional, I by J, frequency table can be calculated from cell residuals as:

$$x^2 = \sum_{i=1}^{I} \sum_{j=1}^{J} \frac{(f_{ij} - F_{ij})^2}{F_{ij}} \qquad [3\text{-}1]$$

where f_{ij} is the observed value in the ij^{th} cell of the table and the F_{ij} is the value fitted under the model. The test value is the squared sum of cell residuals, divided by their expected value F_{ij}. The test value follows a chi-squared -distribution with the degrees of freedom that are the product of the number of classes in *I* minus 1 and in *J* minus 1 i.e. (I-1)(J-1). If the observed cell counts f_{ij} differ greatly from the total independency table, the residuals will increase and the chi-squared test value will increase over the critical value and the null (independency) hypothesis is rejected.

Within the overall test of statistical significance, it is possible to study residuals in individual cells, since cell residuals can indicate what kind of association and how strong the association is between two variables in a multidimensional frequency table. Because the coefficient depends naturally on the overall N, residuals are usually standardised by the standard error of the residuals. Standardised residuals follow the normal distribution and the 95% critical value is two or over for rejecting the null hypothesis that the joint cell contains the number of cases that would be expected in the case of total independence between two variables.[10]

Log linear models generate tables of expected frequencies that can be compared with the observed frequencies using goodness-of-fit tests like chi-squared, but they can be applied to tables of more than two dimensions. A log linear model, in its multiplicative form, writes the expected frequency *F* in each cell *i, j* and *k* of a multidimensional table as a product of a constant term, the main effects of each variable, and the interactions between them. (Powers & Xie 2000). The constant term, main effects and the interaction effects between three variables can be estimated as:

$$F_{ijk} = \eta\tau_i\tau_j\tau_k\tau_{ij}\tau_{ik}\tau_{jk}\tau \qquad [3\text{-}2]$$

The τ-parameters describe the (conditional) probabilities in each cell and margins of the table. Subscripts i=1,...,I indexes the categories of variable A, j=1,..,J indexes the categories of B and k=1,...,K indexes the categories of C. The η is the geometric mean of all frequencies, i.e. it is the reflection of the sample size N. The first three τ-parameters describe the coefficients of one-way effects (merely marginal distributions). τ_i describes the one-way effect of variable A and it refers to a set of parameters that has (I-1) parameters. Consequently τ_j and τ_k describe the one-way effects of variables B and C and they refer to sets of (J-1) and (K-1) parameters. Next three τ-parameters describe two-way effects (or paired associations between variables) and τ_{ij} refers to a set of parameters that has (I-1)*(J-1) parameters, τ_{ik} refer to a set of (I-1)*(K-1) parameters and τ_{jk} refer to a set of (J-1)*(K-1) parameters. The last parameter τ_{ijk} refers to a set of parameters that has (I-1)*(J-1)*(K-1) parameters and this set of parameters describes the 3-way interaction effects. For example, it allows the association between A and B to differ in the categories of C. Since all interaction effects are included in the model, [3-2] describes a saturated model that produces the observed frequencies perfectly. In practise the saturated model is not of much interest because it reproduces the observed data exactly and uses all the available degrees of freedom, so it does not provide a simpler

[10] To be precise, this is only the case with two variables, since a conditional association can remove paired association when variables are adjusted with a third variable.

account of the data. Of more interest are models that fit fewer parameters than the saturated model and which allow us to test specific hypotheses. However, in some cases the saturated log-linear model can be used in the analysis, for example, to study cumulative risk between the forms of deprivation (see Moisio 2002).

By taking natural logarithms from both sides of the equation [3-2], we will have the 'standard' additive log-linear model, where variables are often described by superscripts:

$$\log F_{ijk}^{ABC} = \theta + \lambda_i^A + \lambda_j^B + \lambda_k^C + \lambda_{ij}^{AB} + \lambda_{ik}^{AC} + \lambda_{jk}^{BC} + \lambda_{ijk}^{ABC} \qquad [3\text{-}3]$$

Subscripts i=1,...,I indexes the categories of variable A, j=1,..,J indexes the categories of B and k=1,...,K indexes the categories of C. The θ is the constant, i.e. again the reflection of sample size N. Tests of statistical significance can be performed on individual parameters. For parameter λ_i^A (as well as λ_j^B and λ_k^C) the statistical significance test is not interesting, since the parameter only indicates the skewness of the marginal distribution. But with parameters describing paired association or higher-level interactions, the statistical significance test of parameters and coefficient intervals are the main tools of analysis.

The equation [3-3] is not identifiable without restrictions. In general, for an equation to be identifiable, there have to more cases than unknown parameters in the model. In a log-linear model these cases are cells and the number of parameters for describing the marginal distribution is the number of classes minus one. In a multinomial distribution the number of parameters that is required is the same as the number of parameters needed so that no free cells are left in the multidimensional frequency table. In the log-linear model, the constant term will also require one parameter. The usual way to release the degrees of freedom and this way make a log-linear model identifiable is to set the last category of each variable to be equal to zero, i.e. as a reference class. The degrees of freedom are then calculated simply by subtracting the number of parameters from the number of cells.

Observed cell frequencies are then reproduced with the log-linear equation using some iterative estimation method, for example, a Newton estimation, the iterative proportional fitting (IPF) or Expectation Maximization (EM) algorithm (Bishop & Fienberg & Holland, 1975; Dempster et. al. 1977; Goodman 1979). Estimated cell counts are then compared to the observed ones and the goodness of fit statistics are mobilised to estimate whether the model fit the data. The most widely used goodness of fit test is the likelihood ratio chi-square test (G^2), analogous to the chi-squared test, with the difference that the G^2 is calculated using logarithms from the ratios between observed and expected frequencies, not from the cell residuals as in the chi-squared test value. The goodness of fit tests represent a trade-off against how well the model reproduces the observed data (measured by chi-square or G^2) and the simplicity of the model (measured by the degrees of freedom).

The likelihood ratio chi-square for the goodness of fit test can be calculated using equation 3-4, where f_{ijk} is the observed cell frequency in the cell *ijk* and F_{ijk} is the expected, or estimated, cell frequency of the cell *ijk*. The G^2 test value follows a distribution:

$$G^2 = 2\sum f_{ijk} Log(f_{ijk} / F_{ijk}) \qquad [3\text{-}4]$$

Another common estimate for model fitness is the dissimilarity index (Δ) that shows the proportion of cases that should be moved so that the estimated and observed frequency tables would be identical. (See Vermunt 1997, 74.) Especially in cases when analysing frequency tables with large Ns, or tables with different numbers of observations, the dissimilarity index is perhaps more convenient than the G^2. When the number of cases in the frequency table becomes very large, the G^2 may report statistically significant differences between the observed and estimated tables, though the difference might be in substance insignificant. Also, the G^2 depends on the size of the Ns, so comparing model fitness between tables with different Ns is easier with the dissimilarity index.

The dissimilarity index coefficient for a model can be calculated using the equation 3–5, where the f_{ijk} is, again, the observed cell frequency in the cell *ijk* and F_{ijk} is the estimated cell frequency of the cell *ijk*. The Δ is often multiplied by the value 100 and used as the per centage of misclassified cases:

$$\Delta = \sum \left| f_{ijk} - F_{ijk} \right| \; / (2N) \qquad [3\text{-}5]$$

A log-linear model is usually presented as a group of symbols, representing the variables, that are arranged in a such way as to represent the structure and the associations within the model. For example, the first-order simple Markov chain model for three repeated classifications A, B and C can be presented as:

{A,B,C,AB,BC}

A simple Markov process is thus modelled by removing parameters λ_{ik}^{AC} and λ_{ijk}^{ABC} from the saturated model [3-3]. Omitting these parameters releases (I-1)*(K-1)+ (I-1)*(J-1)*(K-1) degrees of freedom, so the simple Markov model is much simpler than the saturated model. Usually the presentation of a log-linear model follows the hierarchy-principle: if a higher-level term is in the model, all its lower level effects are in the model too, unless the model is defined to be a non-hierarchical model. The simple Markov chain can now be written as:

{AB,BC}

The model shows that there are three variables, A, B and C in the model and A only has an association with B and B only has an association with C. If A, B and C are repeated measurements and we restrict the transition probabilities between A and B and between B and C to be equal (AB=BC), the model describes a time-homogeneous (stationary) first order Markovian process. Now we can test, if necessary, whether this model produces such estimated frequencies that do not differ from observed frequencies. In other words, we can test if the model can explain the associations in the transition table {ABC}.

Hence, when building a log-linear model, we must first clarify the conceptual and causal construction that explains and relates variables to each other. Then a hypothesis about the associations between the variables in the model is made. The hypothesis is then translated into a log-linear model, where variables and parameters are selected, placed and possibly constrained in such a way that the model represents the original conceptual and causal construction. The principal of parsimony guides the model building, in other words, the model is built using as few parameters as possible. After the log-linear model is built, the parameters of the model are estimated and estimated frequencies are produced by solving the log-linear equation using a maximum-likelihood method. Estimated frequencies are then compared to observed frequencies and the fitness of the model is evaluated by diagnostic estimates. If the model fits adequately and cell residuals do not indicate any problems, then the coefficients and statistical significances of the parameters are studied and the model is interpreted.

Fitting and modifying a log-linear model is very similar when adding a latent variable into the model. The difference is that a log-linear model with latent variables reproduced an estimated frequency table that has more dimensions than the observed frequency table has. In other words, the latent variable(s) only exist(s) as link functions in the log-linear equation and the goodness of fit -test is made possible by collapsing the reproduced table over the classes of latent variable(s). This will cause some additional difficulties concerning the identifiability of the model in Latent Class modelling, as we will see in the next section.

3.5.3 Latent variable extension to log-linear models

3.5.3.1 Latent Structure Models

Interpreting an association between two variables is fairly easy, although it already requires a theoretical construction for the interpretation to build on. Paired associations can be, for example, visualised using scatter plot, box-plot or clustered bar charts. But when the number of variables increase, the number of their paired associations also increase and interpreting these multiple associations becomes difficult.[11] If we want to take possible conditional associations into consideration, as we usually do in sociology, then the number of associations, paired and conditional, increase rapidly.[12] For example, a measurement model with five variables has 50 possible paired and conditional associations. This applies only to the interval level variables. With polychotomous categorical variables, the number of parameters describing paired and conditional associations increase even more rapidly when the number of variables increase, because more than one parameter is needed to describe the association between the two variables. This means that making a reliable interpretation about the associations between even fairly small numbers of variables is already quite inconceivable, unless we have some method to overcome this natural limitation of human perception.

The problem of interpreting multiple and simultaneous associations between variables gave rise to the idea that there may be only a few factors in the explanation behind these observed associations. These explanatory factors were thought to be some kind of latent variables, which cannot be directly measured, but only estimated from the observed variables using mathematical functions. The first steps toward investigating latent variables were taken in the 1920s, when Spearman formulated a theory presenting the idea that observed associations between numerous ability tests can be explained by one general (g) factor. For example, positive correlations between paper and pen ability tests can be explained by one latent factor - intelligence. A few decades later Thurstone extended this theory to include multiple factors and developed a method of rotating the axes. Using this factor analysis, it was now possible to create latent variables and to calculate a person's score within them. With multiple factors, the theory extended from the study of ability to the measurement of personality. Finally, factor analysis found its way into the social sciences and gained popularity in the 1960s and 1970s as a general exploratory factor analysis. (Bollen 1989.)

[11] It is easy to illustrate that the number of paired associations increase as a numerical series 1,3,6,10,15,21... when the number of variables increase starting from two following arithmetic formula $A = (N-1) + A_{N-1}$, where N is the number of variables and A is the number of associations.

[12] The number of paired and conditional associations increase geometrically, following the formula $A = ((N-1) + A_{N-1}) * N$, when the number of variables increase. The numerical series describing this increase is 2,9,16,50,90,147... when the number of variables increase starting from two.

However, exploratory factor analysis is very easy to misuse, for example, the axes rotation can be manipulated to get the desired result. It was the misuse and casual application of exploratory factor analysis in the social sciences that led to increasing criticism towards it. In the 1960s a more sophisticated type of factor analysis method was created in answer to the aforementioned problems of exploratory factor analysis. Jöreskog (1969) developed the confirmatory factor analysis method that lifted factor analysis into a higher theoretical level than it had been in with exploratory factor analyses. In the latter, the latent factor was merely used as a tool for data reduction, but in confirmatory factor analysis, the latent variable resembled a pure concept or abstraction. This abstraction has to be derived from a theory before actual analysis, because its compatibility and construction are 'tested' against empirical data. The testing of constructed relationships between the latent variable(s) and observed variables gave the name 'confirmatory' to this type of factor analysis.

A parallel development took place at the same time among sociologists - Lazarsfeld and Henry (1968) were developing a measurement model that could relate the latent variable to the observed variables. As sociologists they were more interested in developing measurement models for categorical variables, since many of the most important concepts in sociology cannot be measured as continuous or interval level variables (e.g. gender and social class). They created and defined the method of *latent structure analysis*, which included a large family of *latent structure models* designed for nominal, ordinal and discrete interval or ratio level manifest variables.[13] Latent structure analysis is based on the idea that constructed latent structure is tested against the data,[14] so it follows the logic of confirmatory factor analysis from its beginnings. Despite the similar heuristic foundations (i.e. confirming the latent structure), these two methods of analysis were developed for different kinds of measurement situations and objects. This is the reason why in this section, the confirmatory factor analysis and other *structural equations models* (e.g. LISREL models) for continuous manifest variables are given much less attention than the latent structure models with discrete latent and manifest variables.

Here, latent structure models are interpreted using Lazarsfeld and Henry's (1968, 15–7) definition. In general, they defined latent structure models as measurement models that relate the discrete or continuous latent variable(s) to the discrete scores or categories of manifest variables. There can be more than one latent variable, but often only one latent variable is assumed in the latent structure

[13] This definition follows Bartholomew's (1987) definition that latent structure models are latent variable models with categorical latent variable(s) and discrete or continuous manifest variables. However, Lazarsfeld and Henry (1968) also included in some cases models with continuous latent and/or manifest variables into the family of latent structure models.

[14] However, there are presentations on how to use the latent structure analysis in an exploratory way e.g. Goodman (1978).

model. They also stated that the relations between the latent variable and manifest variables are stochastic. The relationships between latent and manifest variables are accounted for by probabilistic relationships. These probabilistic relationships are treated under the axiom of local independence.

The axiom of local independence, formulated by Lazarsfeld and Henry (1968, 17), can be seen as the defining characteristic of latent structure models. In every latent structure model it is assumed that the observed associations between manifest variables depend on the relationship between latent and manifest variables. This means that if we standardise manifest variables using the latent variable, associations between manifest variables should become locally independent. Thus, the axiom of local independence assumes that if we hold the latent variable constant, manifest variables should be statistically independent from each other (Heinen 1996, 6). It is assumed that this 'additional' latent variable explains the observed relationships (McCutcheon 1987, 16). Thus, the axiom of local independence assumes causality from the latent variable(s) to the observed variables, even if no causal assumption is made on the nature of an association between manifest variables.

Hence, latent structure models are heavily loaded measurement models both in the perspective of mathematics as well as epistemology. The axiom of local independence makes it possible to estimate a statistical model where a latent variable is modelled behind the observed response pattern (or correlation or covariance matrix). The constructed theoretical background that explains what this latent variable is and why it relates to the observed variables the way it does will give life to these mathematical functions.

3.5.3.2 Latent Class Modelling

Latent Class modelling is built around the axiom of local independence. The axiom of local independence is, in fact, based on the simple idea of elaboration. If we think that two variables are supposed to measure the same thing, for example two opinion statements on certain political decisions, they should be 'locally' independent from each other if we held the latent 'political orientation' -variable constant. This follows the statistical inference of elaboration, where the relationship between A and B is explainable due to C, if the relationship between A and B disappears when C is held constant – or in the case of C being categorical, if the relationship between A and B disappears in the categories of C. In other words, A and B are locally (conditionally) independent in the classes of C. This line of inference also holds when C is an unobserved, that is, latent variable. The only difference with a latent variable C is that we cannot now allocate the sample into the categories of C for elaboration – elaboration with a latent variable has to be done with the linear equations of the latent structure model.

It can be said that the latent class (LC) model is a log-linear model where there are more dimensions in the estimated frequency table than there are in the observed frequency table. Presentation and estimation of the LC model thus follows the presentation and estimation of the log-linear model. The observed frequencies are reproduced by conditional probabilities using the following equation [3-4], the mathematical formalisation of the axiom of local independence, which can be seen as the main characteristic of the LC model:

$$P(X=t \mid ABC) = \pi_{ijkt}^{ABC\overline{X}} = \frac{\pi_{ijkt}^{ABCX}}{\sum_{t} \pi_{ijkt}^{ABCX}} \qquad [3\text{-}4]$$

Subscripts i=1,...,I indexes the categories of A, j=1,..,J indexes the categories of B, k=1,...,K indexes the categories of C and t=1,...,T indexes the categories of the latent variable X. The equation [3-4] expresses the conditional probabilities that a given case is located in the i, j, k^{th} cell in the observed response pattern when the latent class t=1,...,T is given. The conditional probability of belonging the i, j, k^{th} cell when X is known, $\pi_{ijkt}^{ABC\overline{X}}$, is calculated by dividing the latent probabilities belonging to the i, j, k,t^{th} cell in ABCX table, π_{ijkt}^{ABCX}, by the sum of these probabilities over the t latent classes. In other words, the equation explains all the associations between observed variables by their association with a latent variable. Equation [3-4] represents a LC model with one variable, but it can be extended to encompass more than one latent variable; however, the equation becomes longer and much more difficult to grasp at a glance.

The presentation and estimation of the LC model is straightforward, and model building is very similar to the building of a log-linear model. The log-linear equation of a LC model expresses the expected frequency F in the i, j, k,t^{th} cell ABCX table as:

$$\log F_{ijkt}^{ABCX} = \theta + \lambda_i^A + \lambda_j^B + \lambda_k^C + \lambda_t^X + \lambda_{it}^{AX} + \lambda_{jt}^{BX} + \lambda_{kt}^{CX} \qquad [3\text{-}5]$$

Manifest variables A, B and C, and the latent variable X, are described by superscripts. Subscripts i=1,...,I indexes the categories of A, j=1,..,J indexes the categories of B, k=1,...,K indexes the categories of C and t=1,...,T indexes the categories of X. θ is the constant, i.e. it is the reflection of sample size N. The first three *lamda* (λ) parameters describe the coefficients of main effects (describing marginal distributions) and the next three parameters describe paired associations between the latent variable X and the manifest variables A, B and C.

Because there are no parameters in the equation [3-5] describing associations between the manifest variables, the model tests the hypothesis that relationships between the variables A, B and C can be explained by their relationship to the latent variable X. If this is the case, then we can say that the latent variable X 'explains' the pairwise associations between A, B and C. Parameters in [3-5] have to be constrained so that the equation would be identifiable, as was the case with log-linear models. The usual method is to set the sum of λ parameters to be equal to zero over any subscript. The maximum likelihood estimates for the parameters can be obtained using an iterative EM algorithm (Dempster et. al. 1977). For more detailed insights on the technical and philosophical foundations of Latent Class models, see Goodman (1978), Lazarsfeld & Henry (1968) and McCutcheon (1987).

To obtain maximum likelihood estimates for the LC model the following equations (3-6)–(3-8) have to satisfy equations (3-9)–(3-12) (McCutcheon 1987, 21–27). The equations describe an LC model with three manifest variables A, B and C with a latent variable X. The equation 3-6 presents the estimated probability of an observation being located in the cell *i,j,k,t* (π_{ijkt}^{ABCX}) as the product of the estimated latent conditional probabilities and latent class probabilities. Latent conditional probabilities ($\pi_{it}^{\bar{A}X}, \pi_{jt}^{\bar{B}X}, \pi_{kt}^{\bar{C}X}$) indicate the probability that an observation in latent class t=1,...,T also has a value, for example, i=1, in variable A. Latent class probabilities π_t^X identify the number of latent classes and their relative sizes:

$$\pi_{ijkt}^{ABCX} = \pi_{it}^{\bar{A}X} \pi_{jt}^{\bar{B}X} \pi_{kt}^{\bar{C}X} \pi_t^X \qquad [3\text{-}6]$$

If we sum the equation 3-6 over the latent classes t=1,...,T we will obtain equation 3-7 which provides estimated probabilities for the observed frequency table {ABC}:

$$\pi_{ijk} = \sum_t \pi_{ijkt}^{ABCX} \qquad [3\text{-}7]$$

Since each observed case has to be located into the latent classes with the total probability of 1.00, the conditional probabilities in i=1,...,I, j=1,..,J and k=1,...,K categories have to sum to 1.00 within each latent class t=1,...,T. This is presented in the equation 3-8:

$$\sum_i \pi_{it}^{\bar{A}X} = \sum_j \pi_{jt}^{\bar{B}X} = \sum_k \pi_{kt}^{\bar{C}X} = 1.00 \qquad [3\text{-}8]$$

The iteration for obtaining the maximum likelihood estimates for the LC model parameters is started with initial trial values for the latent conditional probabilities and latent class probabilities in equation [3-6]. These initial values then give an estimate for the π_{ijkt}^{ABCX} that is then used to solve equation [3-7] and equation [3-4] (the axiom of local independence). These initial estimates for the latent conditional probabilities and latent class probabilities are then used in equations [3-9] to [3-12].

In the equations [3-9] to [3-12] the observed cell probabilities in the table {ABC} are presented as p_{ijk} to differentiate from the estimated probabilities, presented as π_{ijk}. By placing the estimated $\pi_{ijkt}^{ABC\overline{X}}$ from equation [3-4] in equation [3-9], we can obtain an estimate for the latent class probability, which determines the probability of a case belonging to the latent class t=1,...,T. The π_t^X also indicates the relative size of the latent classes:

$$\pi_t^X = \sum_{ijk} p_{ijk} \pi_{ijkt}^{ABC\overline{X}} \qquad [3\text{-}9]$$

Latent conditional probabilities are obtained by fitting the solutions from the equations 3-4 and 3-9 into the equations 3-10, 3-11 and 3-12. Equation 3-10 estimates the conditional probability of being in the latent class t=1,...,T when A has the value i=1,...,I. Correspondingly, the equations 3-11 and 3-12 estimate these conditional probabilities for the other two observed variables B and C. Estimates from equations 3-10, 3-11 and 3-12 are placed again in equation 3-6 and a new iteration round starts. The iteration stops when the differences between the estimates at the beginning and at the end of the iteration round are less than a predetermined amount.

$$\pi_{it}^{\overline{A}X} = \frac{\sum_{jk} p_{ijk} \pi_{ijkt}^{ABC\overline{X}}}{\pi_t^X} \qquad [3\text{-}10]$$

$$\pi_{jt}^{\overline{B}X} = \frac{\sum_{ik} p_{ijk} \pi_{ijkt}^{ABC\overline{X}}}{\pi_t^X} \qquad [3\text{-}11]$$

$$\pi_{kt}^{\overline{C}X} = \frac{\sum_{ij} p_{ijk} \pi_{ijkt}^{ABC\overline{X}}}{\pi_t^X} \qquad [3\text{-}12]$$

The degrees of freedom of an unrestricted LC model can be calculated using the formula, [3-13], where I indicates the number of the categories in A, J the number of categories in B, K the number of categories in C and T the number of latent classes in X. The value of the equation [3-13] has to be positive otherwise the LC model is not identifiable. Also, the LC model is prone having local maxima, so the identifiability of the LC model should be always estimated using more than one set of initial values. (McCutcheon 1987, 21–26.)

$$DF = (IJK - 1) - [(I + J + K - 2)T - 1] \qquad [3\text{-}13]$$

The latent class model is often presented as a group of symbols, representing the variables in the model, arranged in such a way as to represent the assumed associations between the variables. The basic LC model, presented in the equation [3-4], can also be presented this way as:

{X,A,B,C,AX,BX,CX}

or, if we follow the hierarchy principle in the model building as is usual, the model can be presented succinctly as:

{AX,BX,CX}

By imposing restrictions to the model we can test various hypothesis about the structure of associations within the panel. For example, by constraining the latent conditional probabilities to be equal (AX=BX=CX) we can test the hypothesis that the probability to belong in the latent class t=1,...,T has the same distribution in the categories of manifest variables i=1,...,I, j=1,..,J and k=1,...,K.

3.5.3.3 Simple, Mixed and Latent Markov Models

Latent class modelling can be used for expanding a simple Markov model into a multiple (Mixed) Markov chains model or into a latent Markov model. Simple, mixed and latent Markov models can be put into a hierarchical order: every mixed Markov model contains at least two simple Markov chains and every latent Markov model contains either a simple or Mixed Markov model. (van de Pol & Langeheine 1990; Breen & Moisio 2004.)

The simple Markov model for one of our four-way poverty transition tables can presented as:

$$F_{ijkl} = N\delta_i \tau_{j|i} \tau_{k|j} \tau_{l|k} \quad [3\text{-}14]$$

where the expected frequency F in the i, j, k, l^{th} cell is presented as a function of the sample size N, initial probabilities δ and transition probabilities τ. Subscript i={1,2} indexes the state of the poor and the not poor at the first wave, j={1,2}, k={1,2} and l={1,2} index the states in the later waves. The δ's indicate the initial distribution over states (probabilities of being in the i={1,2} categories) and the τ's indicate the transition probabilities into a state at $t+1$ given the membership of one or other state at t.

The simple Markov model can be expanded into the mixed Markov model by introducing two or more latent classes into the model. This can be presented as

$$F_{ijkl} = N \sum_{s=1}^{S} \pi_s \delta_{si} \tau_{s,j|i} \tau_{s,k|j} \tau_{s,l|k} \quad [3\text{-}15]$$

The new parameter π_s specifies several Markov processes or chains (indicated by s=1,...,S) and indicates the proportions of the sample in each of the S chains. As the sigma indicates, the expected frequency is now a sum over all the simple Markov chains. We can derive the simple Markov model from the equation [3-15] by setting S=1, but for S >1 the membership of the different chains is defined by latent classes. Another important special case when using this model arises when S=2 and for one of the chains, $\tau_{j|i} = 1$ if j = i, and $\tau_{j|i} = 0$ if $i \neq j$, and similarly for all the other transition probabilities. This special case of a mixed Markov model is the Mover-Stayer model, in which the population is divided into those who never change state and into those who do change states (at least once).

The true and observed values can be separated (and this way measurement error captured) by using the latent Markov model. The model now assumes that to each observation of the states (manifest variables i={1,2}, j={1,2}, k={1,2} and l={1,2}) there corresponds a latent variable which measures the true distribution over the states. These latent variables are specified by the size of the latent classes and the probabilities of being observed in a given manifest class conditional on being in a given latent class. The latent Markov model presented in equation [3-16] is a measurement model that assigns each observed variable to its latent counterpart with probabilistic relationships and assumes independence between the latent variables, as well as between the manifest variables:

$$F_{ijkl} = N \sum_{a=1}^{A} \sum_{b=1}^{B} \sum_{c=1}^{C} \sum_{d=1}^{D} \delta_a \rho_{i|a} \rho_{j|b} \rho_{k|c} \rho_{l|d} \qquad [3\text{-}16]$$

The latent variables are denoted a=1,...,A, b=1,...,B, c=1,...,C and D=1,…,D. The marginal probability distribution in the first latent variable is given by δ and the relationship between the observed variables *I, J, K* and *L* and their latent counterparts, *A, B, C* and *D* is described by the conditional response probabilities ρ. The closer the response probability matrix is to an identity matrix (i.e. $\rho_{manifest|latent}$ =1 when the latent and manifest states are the same, or 0 otherwise) the smaller is the measurement error of the variable. The matrices of ρ parameters can thus be interpreted as measures of reliability.

The structural part of the measurement model does not have to assume independence between the latent variables. We can assume, for example, that the latent variables follow a simple Markovian process. In this case the equation is written as:

$$F_{ijkl} = N \sum_{a=1}^{A} \sum_{b=1}^{B} \sum_{c=1}^{C} \sum_{d=1}^{D} \delta_a \tau_{b|a} \tau_{c|b} \tau_{d|c} \rho_{i|a} \rho_{j|b} \rho_{k|c} \rho_{l|d} \qquad [3\text{-}17]$$

where the τ's now indicate the transition probabilities between the latent variables, hence serving the function in the latent Markov model as the τ's in the simple or mixed Markov model. So the latent Markov model [3-17] contains the structural model (simple Markov chain) and a measurement model that describes how the manifest and latent variables are related. Model [3-16] can be derived from [3-17] by imposing the constraint that the matrices of parameters are all identity matrices.

Lastly, we can assume that the structural part of the measurement model is a mixed Markov model. This can be presented as:

$$F_{ijkl} = N \sum_{s=1}^{S} \sum_{a=1}^{A} \sum_{b=1}^{B} \sum_{c=1}^{C} \sum_{d=1}^{D} \pi_s \delta_{sa} \tau_{s,b|a} \tau_{s,c|b} \tau_{s,d|c} \rho_{s,i|a} \rho_{s,j|b} \rho_{s,k|c} \rho_{s,l|d} \qquad [3\text{-}18]$$

The latent mixed Markov model is a group of latent simple Markov processes indexed by s=1,...,S, each of which can have its own measurement part in the model. For example, in the latent Mover-Stayer model we can assign different reliabilities for the movers and for the stayers.

Maximum likelihood estimates of models 3-14 to 3-18 can be found using the EM algorithm (Dempster et. al. 1977). However, many latent class models will not be identified because they will require more parameters than there are degrees of freedom. Even when this is not the case, identification may be a problem. For example, for any latent Markov chain over three or more waves, the reliability matrices (ρ's) of the first and last waves will not be identified (Van de Pol and de Leeuw 1986: 126). Goodman (1974b) provides a rank test for the identifiability of simple latent class models. All the models used in the following empirical chapters are fully identified.

The latent (mixed) Markov model can be used for correcting the over-estimation of mobility in panel data by breaking down the observed change and stability into true and error components using the parameter estimates of the model. Using the terminology of Langeheine and van de Pol (1990) in the model [3-19], the total proportion of stability (TOS) is the proportion of cases remaining in their original state throughout the observation period, expressed as a proportion of the total sample. Hence, TOS indicates true stability. In the model [3-20] the TRS, or 'true observed stability', can be thought of as the proportion of true stability TOS that is observed as stability. The difference between TOS and TRS is error. The formulae for these are:

$$TOS = \pi_{s=1} \sum_{a=1}^{A} \delta_a \tau_{b|a} \tau_{c|b} \tau_{d|c} \qquad [3\text{-}19]$$

$$TRS = \sum_{a=1}^{A} \sum_{b=1}^{B} \sum_{c=1}^{C} \sum_{d=1}^{D} \pi_{s=1} \delta_a \tau_{b|a} \tau_{c|b} \tau_{d|c} \left(\rho_{i|a}\right)^4 \qquad [3\text{-}20]$$

(i=a, j=b, k=c, l=d, a=b=c=d in 3-19 and 3-20)

Observed change itself can be deconstructed in a similar way. Total change, TOC, indicates true change and it can be calculated as: TOS + Perfect Stability + TOC = 100%. Perfect stability is the proportion of stayers in the Latent Mover-Stayer model that are assumed to be measured perfectly. TOC can be partitioned into true observed change TRC and error. TRC is the proportion of true change TOC which is observed as such:

$$TRC = \sum_{a=1}^{A} \sum_{b=1}^{B} \sum_{c=1}^{C} \sum_{d=1}^{D} \pi_{s=1} \delta_{a} \tau_{b|a} \tau_{c|b} \tau_{d|c} \left(\rho_{i|a}\right)^{4} \qquad [3\text{-}21]$$

(i=a, j=b, k=c, l=d, not a=b=c=d)

By comparing the true observed stability (TRS) and true observed change (TRC) to the true stability (TOS) and the true change (TOC) we can estimate how much the random error increases the observed estimates of mobility in our poverty transition tables.

3.6 Conclusions

In the third chapter we presented the research hypotheses, the data and the methods of the study. We started by presenting the four research hypotheses that this study tries to falsify. These hypotheses were derived from several influential theories on poverty and social mobility research. The first hypothesis tests the assumption that the population is heterogeneous in relation to the transition of poverty. This hypothesis is derived from the individualisation thesis that argues that in the affluent welfare states poverty touches even the middle classes, implying that poverty incidences are somewhat equally distributed throughout the population. The second research hypothesis states that poverty mobility is over-estimated in panel data if random error is not taken into account. This thesis is based on classical test theory and on the previous studies that have shown that random error causes an over-estimation of mobility in panel data. The third hypothesis states that the dynamics of poverty are common across direct, indirect and subjective deprivation measures. This hypothesis is based on the thesis that direct and indirect head-count poverty indicators measure the same dynamic process, but in its different phases. The fourth research hypothesis states that poverty dynamics are common across countries. This hypothesis is based on recent empirical studies, which have indicated that many countries have surprisingly similar patterns of relative poverty mobility, despite large differences in their cross-sectional poverty figures.

After presenting the research hypotheses, section three presents the data and variables. As in many contemporary European level longitudinal poverty studies, this study uses the European Community Household Panel (ECHP) as the data. Ten EU countries are selected for analysis. Three well-known direct, indirect and subjective head-count poverty and deprivation classifications are selected, and used in four repeated measurements between 1994–1997: relative financial poverty, housing deprivation and the subjective deprivation measure.

The descriptive figures that these three indicators give are presented in section four. The preliminary findings from these figures are that poverty and deprivation dynamics seem to have following characteristics. First, poverty and deprivation spells are usually relatively short in duration, but they touch quite a large part of the population. Secondly, even a single poverty or deprivation incidence will mean that the risk of poverty will stay high for years. Thirdly, the majority of the population never experience poverty or deprivation and only a small fraction live in constant poverty or deprivation. A model that could explain this kind of dynamic structure would assume that the population is divided into the three groups of people. The first group would be those who will never experience poverty and they would form the majority of population. The second group would be a small group of people who live in constant poverty. The third group would be a movers' group, 20–40 per cent of the population, whose members move in and out of poverty and because of this, live with a constant and relatively high risk of poverty.

To answer whether this preliminary model is correct, and to test the original research hypotheses, we need more sophisticated methods than were used to gain the descriptive poverty figures. For this, in section five, the family of Markov chain models was presented as a toolbox for modelling poverty dynamics in a discrete time and space. Simple, Mixed and Latent Markov models were presented and it was described how they can be converted into testable log-linear models. The simple Markov model assumes that there is a homogenous population, in other words, the model assumes that the population has one common trajectory in their poverty transitions. The Mixed Markov model, on the other hand, tests the assumption that the population is heterogeneous and that the different groups in the population follow their own separate simple Markov process. Finally, we showed how a Latent Mixed Markov model can be used as a genuine measurement model, containing a structural part and a measurement part, to separate the true change from the error and in this way estimate how much observed poverty mobility is over-estimated because of random error. To summarise, section five showed that by embedding latent variables into log-linear models we get a powerful and flexible tool that will now be used in the following chapters to model and compare the dynamics of poverty and deprivation.

4 Modelling the dynamics of poverty

4.1 Introduction

Four research hypotheses were formulated in the previous chapter. In this fourth chapter we test empirically the first two of them. The first research hypothesis states that the transition of poverty (poverty fluidity) is not common across the population, in other words, the population is heterogeneous in its relation to poverty transition. The descriptive poverty and deprivation figures have already indicated that a part of the population seems to have a permanent high-risk poverty trajectory, while the majority has a permanent low-risk poverty trajectory. So if we can model the transitions of poverty and deprivation only with a model that assumes a heterogeneous population, then we can accept the hypothesis that there are different poverty trajectories in the population. In this way we can also test, though indirectly, the individualisation thesis: if the proportion of stayers (either in poverty or not in poverty) is high in the population, it indicates that poverty is (still) very much a non-transitory and structural phenomenon. The second research hypothesis states that poverty mobility is over-estimated if random error is not taken into account. Based on previous studies, we expect that a part of the observed poverty mobility in our transition tables will be caused by random error. We try to estimate the size of this over-estimation by using measurement models that allow for error in the measurement.

The research hypotheses are converted into testable models using log-linear modelling techniques, presented in the preceding chapter. Several Simple, Mixed and Latent Markov models, as well as some Latent Class and Independence models, are fitted separately for each country. The set of models is first fitted to the financial poverty transition tables in section two, then to the housing deprivation tables in section three and finally to the subjective deprivation transition tables in section four. A Latent Markov model (that has a Mixed Markov model as the structural part) is able to describe satisfactorily associations observed in the financial poverty, deprivation and subjective deprivation transition tables. Using the parameter estimates of this measurement model we estimate the true stability and change in the transition tables. The fifth section summarises the results of the chapter.

4.2 Dynamics of financial poverty

4.2.1 Modelling poverty transition with Latent Class and Markov models

Following the suggestion of Langeheine and van de Pol (1990), we try to improve the fitness of a Simple Markov chain model by allowing both the heterogeneous population and measurement error into the model, turning a Simple Markov model eventually into a Latent Mixed Markov model.[15] All the Markov models that will now be presented describe a first-order (latent) Markovian process. The Markov models are first tested with the usual equality restrictions on the (latent) transition probability matrixes. (In Latent Class models, equality restrictions are imposed to the latent conditional probability matrixes.) The equality constraint on the (latent) transition probabilities would simplify the Markovian process to the extreme by assuming that the transitions from one wave to another are common, in other words, the Markovian process would be unchangeable through time. This assumption about the Markovian process being unchangeable would help us to present and interpret financial poverty fluidity. But the variation in the transition probabilities from one wave to another is substantial (as we will see in the Table 4.2.1), so we cannot assume that poverty transitions are invariant. It seems that we have to allow poverty transitions from measurement point *t* to *t+1* to vary, in other words, to allow the two-way transition probabilities to be non-stationary. However, the model fitness diagnostics of the original constrained Markov (and LC) models are presented before testing the same models without restrictions. All the tested models are identifiable and no local maxims were detected. The LEM syntaxes for all models are presented in the Appendix A.

Table 4.2.1 presents the model fit diagnostics of twelve models that each contain a set of assumptions about the stochastic process that was suspected to lie under the observed financial poverty transition. We start the model fitting with two models, the Independence and Quasi-Independence models, that actually assume no process or connection between the measurement points. These models with their rather extreme assumptions about the transition in the panel, or better, lack of it, are a reference point or a yardstick for the actual Markovian chain modelling. The Independence model can be viewed as a Markov model where all transition parameters are omitted: the model tests the hypothesis that there are no associations between the repeated measurements. In other words, the Independence model assumes that an incidence of poverty is independent from the previous situation(s).

[15] The third path to improve the goodness of fit of a Markov chain model would be to allow higher-level interactions to the transition chain, but we do not use this method, mainly because a second or higher order Markov chain no longer simplifies the stochastic process by much, as was discussed earlier.

TABLE 4.2.1: Markov and Latent Markov Models for financial poverty dynamics

		DK		NL		B		F		IRL		I		EL		E		P		UK	
Model	df	G2	Delta	G2	Delta	G2	Delta	G2	Delta	G2	Delta	G2	Delta	G2	Delta	G2	Delta	G2	Delta	G2	Delta
(1) Independence	11	1 856,6	15,2	6 078,6	23,1	6 600,8	34,5	14 515,5	34,5	7 317,9	32,3	13 367,4	31,8	10 755,5	38,2	9 103,8	29,1	14 037,4	40	10 386,2	37,1
(2) Q-Independ.	9	191,1	3,2	306,6	3,2	370,5	4,7	432,9	3,3	488,0	5,1	524,8	3,5	638,6	5,1	245,2	2,6	516,4	4,5	766,6	6,4
(3) Simple Markov	12	565,7	7,9	708,2	6,0	854,2	9,2	1566,5	8,8	935,5	8,3	1993,1	10,7	1124,6	9,8	2685,6	14,0	1718,5	11,5	765,8	7,3
(4) Simple Markov*	8	371,0	5,6	660,1	5,5	804,6	9,0	1524,7	9,0	926,4	8,4	1983,6	10,6	1059,1	9,8	2566,1	13,8	1637,8	11,3	701,4	7,6
(5) Markov 2 chain	8	305,4	4,8	106,4	2,0	187,2	3,2	136,5	1,8	119,0	2,5	229,2	2,6	109,6	1,7	236,4	2,9	251,3	2,9	108,9	2,2
(6) Mov-Stayer	10	333,2	4,9	110,8	2,0	200,8	3,6	136,5	1,8	218,1	3,0	229,2	2,6	227,3	3,2	281,9	3,2	254,1	2,9	134,9	2,6
(7) Mov-Stayer*	6	111,0	2,6	64,4	1,2	146,2	2,6	88,2	1,4	210,1	3,0	214,6	2,5	168,6	2,9	144,9	2,5	178,9	2,3	57,8	1,5
(8) LC	12	373,5	5,9	349,8	3,8	336,8	5,2	613,7	4,8	555,6	5,7	459,3	4,0	519,1	4,7	579,9	4,5	712,8	5,6	786,6	6,9
(9) LC*	6	76,4	1,8	175,2	2,2	213,8	3,9	474	3,8	395,6	4,3	390,8	3,3	336,2	3,8	477,5	3,9	505,5	4,7	424,4	4,5
(10) Lat. Markov	10	262,1	4,6	120,3	2,1	175,8	3,2	287,5	3,1	213,1	2,6	159,8	2,3	166,8	2,5	570,9	4,2	238,6	3,5	206,0	3,0
(11) Lat. Markov*	6	46,5	1,3	83,5	1,8	157,2	2,9	245,0	2,6	191,0	2,6	122,6	1,8	128,5	2,1	529,3	3,7	219,7	3,2	145,3	2,6
(12) Lat.Mov-Sta*	4	34,7	1,1	7,0	0,5	56,6	1,9	25,4	0,7	130,1	2,0	22,8	0,7	69,3	1,5	126	2,1	68,7	1,5	17,1	0,8

* The (latent) transition/conditional probabilities are not set equal between waves.

The Independence model, or more precisely, its mismatch with the observed table, shows how strong associations are in a transition table. We can interpret the likelihood-ratio (G^2) value and dissimilarity index (Δ) value of Independence model as indicators of how deterministic poverty is on the transition table. When observing the proportion of misclassification (Δ) in the Table 4.2.1, it seems that the financial poverty transition is least deterministic in Denmark and most deterministic in Portugal.[16] With 11 degrees of freedom, the Independence model has the G^2 value of 1 856.6 and the Δ value of 15.2 in Denmark. In Portugal, the corresponding values are (G^2) 14 037.4 and (Δ) 40.0. In other words, an incidence of financial poverty seems to predict financial poverty in the near future most strongly in Portugal, while in Denmark current poverty status is a much weaker predictor of poverty than in Portugal.

The Quasi-Independence model tests the hypothesis that those who move, move randomly. In other words, only two interaction parameters, located in the two non-movers cells, are estimated for describing all the associations in the n-way transition tables.[17] The Quasi-Independence model has 9 degrees of freedom and the dissimilarity index (Δ) indicates that the model misclassifies fewer cases than the Independence model. The Quasi-Independence model seems to have the best fit in the Spanish table (G^2=245.2; Δ=2.6) and the poorest fit in the UK table (G^2=766.6; Δ=6.4). When comparing the differences in the model fit of the Independence and Quasi-Independence models, we can conclude that there are large differences between countries in their total poverty mobility at the population level, but the differences in poverty mobility are smaller between countries when we study just those who have experienced poverty. In other words, those who have experienced a poverty incidence at least once and this way have moved across the poverty threshold (at least once) in the panel seem to move as randomly in every country.

The Simple Markov chain model (model 3) releases the associations between two successive waves describing the basic first-order Markovian process. Simple Markov and Simple Markov* models test the hypothesis that only the situation at time *t*-1 has an effect on the current situation at time *t*. Both models also assume that there is a homogeneous population. In other words, models assume that everybody in the population follows the same poverty trajectory. The Simple Markov model has its two-way transition matrixes restricted to be equal, i.e. stationary. In the Simple Markov* model, the stationarity constraint is removed.

[16] When comparing countries here it is safer to rely on the dissimilarity index than to the likelihood-ratio, since the likelihood-ratio also reflects the sample size. We could standardise the likelihood-ratios by Ns, as will be done in chapter six, but this standardisation is not done here, because the main goal here is to model poverty transitions, not compare countries.

[17] Thus the Quasi-Independence model is not assuming independence between t and t+1 in the total population, it assumes total independence only among those who change their poverty status at least once between time t and t+n.

The Simple Markov model has quite a poor fit in every country. The best fit can be found in the Dutch table, where the Simple Markov model has the G^2 value of 708.2 with 12 degrees of freedom, misclassification being 6.0 per cent of all cases. The largest mismatch can be found in the Spanish table where the G^2 value is 2685.6 and the misclassification is 14.0 per cent of all cases. Removing the stationarity constraint from the two-way transition matrixes takes four degrees of freedom, but it improves the model fit only little. In most of the countries, relaxing the stationarity assumption does not improve the fitness at all. The unrestricted Simple Markov* model has 8 degrees of freedom and the best fit can be found again in the Dutch table (G^2=660.1; Δ=5.5) and the poorest fit (again) in the Spanish table (G^2=2566.1; Δ=13.8). So it seems that with or without the stationarity constraint on the transition probabilities, the single chain (first-order) Markov chain model is incapable of describing the observed associations in the financial poverty transition tables. The mismatch between the observed and estimated cell frequencies is around ten per cent in most of the countries. This suggests that the population might not be homogenous in relation to the transition of poverty and that there is more than one poverty trajectory, or process, that the population follows.

We can allow the population to be heterogeneous by increasing the number of chains in the Markov model. Models 5, 6 and 7 are Mixed Markov models that contain two simple Markov chains. There are no degrees of freedom left to estimate a Markov model with two chains without some restrictions on the transition matrixes, so the Markov 2 chain model is the combination of two stationary Simple Markov chains. The Markov 2 chain model has 8 degrees of freedom and it has a relatively good fit in some countries. For example, in Greece the G^2 value is 109.6 and the misclassification is 1.7 per cent of all cases. The Markov 2 chain model has the poorest fit in the Danish table (G^2=305.4; Δ=4.8). If we constrain the transition probability matrixes of the second chain in a two chain Markov model to be an identity matrix, we get the classical Mover-Stayer model. The Mover-Stayer model simplifies the transition process into a model with an easily written description: the model explains the observed transition with the model that there are two non-mover groups, never in poverty and always in poverty, and between these non-mover groups there is a group of movers that follow a simple Markov chain. However, the Mover-Stayer model where the movers' chain is constrained to be stationary does not have a particularly good fit in most of the countries. The stationary Mover-Stayer model has 10 degrees of freedom and the best fit can be found in the French table, where the G^2 has value 136.5 with the Δ value of 1.8 per cent. In the rest of the countries, the stationary Mover-Stayer model misclassifies 2 per cent or over of the all cases. The poor fit is probably due the stationarity restriction, since already with the Simple Markov model we discovered that that the poverty transition probabilities are not constant over time. So in the Mover-Stayer* model, we remove the stationarity restriction from the movers' chain. This takes four degrees of freedom, leaving 6 degrees of freedom to be used. The time-heterogeneous Mover-Stayer* model has quite a good fit in many countries. The best fit can be found in the Dutch table, where the likelihood ratio has the value 64.4 and the misclassification is 1.2 per cent. In the rest of the countries the misclassifications remain below 3 per cent, except in Ireland where the Δ value is exactly 3.0 per cent.

It seems obvious that the population is heterogeneous with respect to poverty transitions. But just allowing the population to be heterogeneous does not seem to be enough to make a Markov model fit the data. The next step to improve the model fitness would be to allow the Mixed Markov model to measure poverty transition imperfectly, just like Langeheine and van de Pol (1990) suggested. Before we begin to use actual measurement models, with error, we should introduce two models that isolate the measurement error that we expect to responsible for the mismatch between the model and the observed dynamics. For this purpose we fit to our transition tables two Latent Class (LC) models, which both have two latent classes. The LC model tests the extreme hypothesis that there is no true change in the panel, instead, all observed transitions are simply error. The eighth model is a stationary Latent Class model in which all the reliabilities are constant over time. It tests the assumption that (i) there are two classes of people in the population, poor and non-poor, and (ii) people do not change their class in the panel. All the observed transitions are assumed to be misclassifications. The stationary LC model has 12 degrees of freedom and the model does not have a particularly good fit in any of the countries: in most of the cases misclassifications vary between four and seven per cent. The unstationary LC* model (where the reliabilities can vary between measurement points) has 6 degrees of freedom and it fits much better with the data than the stationary LC model. The best fit is found in Denmark, where the G^2 value is 76.4 and the dissimilarity index value is less than two per cent. However, bearing in mind the rather extreme hypothesis that these models represent, i.e. that all observed transitions are error, the fit of the unrestricted LC* model is strikingly good. This indicates that a substantial part of the observed mobility in our financial poverty transition tables is due to measurement error. That is, a non-mobile case (either never in poverty or always in poverty) is misclassified as poor while really non-poor or as non-poor while really poor in one (or more) of the measurement points.

In the last three models (models 10, 11 and 12) we incorporate measurement error in the Markov chain model by constructing a measurement model that contains a measurement part and a structural part. The structural part represents the associations between the variables, which are assumed to follow a Markovian process. The measurement part defines the probabilistic way that every observed variable relates to (i.e. measures) the structural component of the model. The structural parts in the stationary and in the time-heterogeneous Latent Markov models (models 10 and 11) are direct counterparts to the stationary and the time-heterogeneous Markov models, as the structural part of the time-heterogeneous Latent Mover-Stayer model (model 12) is the direct counterpart to the time-heterogeneous Mover-Stayer model. In other words, in these three Latent (Mixed) Markov models, the Simple Markov chain(s) is a latent structure and the observed measurements are related to this structure with probabilistic relationships, allowing for error in the measurement. In all three Latent Markov models we set the reliabilities (probability matrixes between the observed measure and its latent counterpart) to be time-homogenous.

The stationary Latent Markov model (model 10), where the latent transitions are set to be stationary, has 10 degrees of freedom. The model has the best fit in the Dutch panel (G^2=120.3; Δ=2.1), but in the other countries the mismatch is substantially higher. The (Simple) Latent Markov model is clearly unable to describe the observed association in the financial poverty transition tables. However, when comparing the misclassifications (Δ) of the (Simple) Latent Markov model to the misclassifications produced by the Simple Markov model (model 1), we see that taking into account measurement error we improve the fit by between 24 and 79 per cent, depending on the country. Furthermore, the time-heterogeneous (Simple) Latent Markov* model (model 11) decreases the misclassifications to a fraction of those produced by the Simple Markov models (stationary or time-heterogeneous). These results strongly confirm our suspicion that random error plays a substantial part in observed mobility and causes serious mismatches between the model and the data.

However, it seems that taking measurement error alone into account is not enough to achieve an adequate model fit. The good fit of the time-heterogeneous Mover-Stayer* model (model 7) indicates that the population is heterogeneous and that poverty transitions are time-heterogeneous, so, in the final model, we allow for error as well as population and transition heterogeneity in the model – or, to be more precise, in the structural part of the model. The time-heterogeneous (partially) Latent Mover-Stayer model* (where the movers' chain is time-heterogeneous) assumes that the stayers are measured without error and the reliabilities for the movers are time homogenous. In other words, the model allows constant error when estimating the movers' states, but assumes that the stayers are measured perfectly. The time-heterogeneous Latent Mover-Stayer model has 4 degrees of freedom and yields a good fit to most countries' tables. Δ is two per cent or less in every example except in Spain where it is 2.1 and in the Dutch, French, Italian and British tables, less than one per cent. Although the G^2 values indicate that there are statistically significant differences (at the .05 level) between the estimated and observed frequencies (except in the Netherlands), taking into account the sample size and the nature of our frequency tables (transition tables), this degree of fit seems satisfactory. We therefore conclude that the poverty dynamics seem to follow a process that can be described by the time-heterogeneous Mover-Stayer model that allows for error in the measurement of the movers' poverty state.[18]

Before we accepted this model as our final model, we tested also a model that placed no constraints on the stayers' reliabilities (except that they are time-homogeneous), i.e. the model assumed separate error for the stayers chain. Releasing the reliability matrices in the stayers' chain took two degrees of freedom, but it did not improve the model fit. So, from the two models with the same goodness of fit, we chose the simpler model for the analysis. This follows the principle of parsimonious in the model-building. The simpler model is the Latent Mover-Stayer model with no error in the stayers' chain.

4.2.2 Error corrected estimates for poverty dynamics

Table 4.2.2 presents the estimated parameter values of the final time-heterogeneous (partially) Latent Mover-Stayer model. The first column shows the π coefficients that indicate the proportions of movers and stayers in the population. When observing the πs we can see that there are large differences in the proportions of movers and stayers between countries. In some countries the proportion of movers is large, as in Denmark, the Netherlands and Portugal. In some countries the proportion of movers is relatively small, as in Belgium, France and Spain. The initial probabilities δ indicate how many movers (or stayers) are classified as poor and how many as non-poor in the first measurement point. The initial probabilities show that over 90 per cent of the stayers are classified as non-poor in the first measurement point, except in the Netherlands (85%), in Ireland (89%) and in Portugal (66%). In other words, in most of the countries, the clear majority of stayers are non-poor. We can calculate the proportion of these stayers who will never be observed in poverty in the total population by multiplying π with δ. The products of these calculations are presented in the Table 4.2.2. We can see that the highest proportions of those who are never in poverty can be found in Belgium and in France, 59 and 58 per cent. The lowest proportions can be observed in Denmark, 18 per cent, in the Netherlands, 15 per cent, and in Portugal, 16 per cent. The percentage that will always be observed as poor is highest in Portugal at eight per cent (0.24*0.34), then in France at five per cent (0.63*0.08).

The response probabilities (ρ) relate the manifest variables to the latent variables and it is here where the measurement model takes error into account. The modal response probabilities in the diagonal of the ρ matrix can be treated as reliabilities, and the non-modal as error, so we have separate reliability estimates for the poor and the non-poor. It is perhaps not surprising that there seems to be

[18] Also McCall (1971) found that a Mixed Markov model is better than a Simple Markov model in explaining the low-income dynamics in the US between the years 1957 and 1966.

TABLE 4.2.2: Estimated Parameter Values for Partially Latent Movers-Stayers Model in Financial poverty tables

Country	Chain proportion Chain	π	Initial proportion Class	δ	Latent Transition Probabilities τ t to t+1 Class 1	Class 2	Class 1	Class 2	Class 1	Class 2	Response probabilities non-poor	poor
DK	Mover	0,81	Class 1	0,88	1,00	0,00	0,97	0,03	0,86	0,14	0,98	0,02
			Class 2	0,12	0,24	0,76	0,16	0,84	0,07	0,93	0,38	0,62
	Stayer	0,20	Class 1	0,94	1,00	0,00	1,00	0,00	1,00	0,00	1,00	0,00
			Class 2	0,06	0,00	1,00	0,00	1,00	0,00	1,00	0,00	1,00
NL	Mover	0,83	Class 1	0,86	0,93	0,07	0,98	0,02	0,95	0,05	0,99	0,01
			Class 2	0,14	0,28	0,72	0,24	0,76	0,23	0,77	0,32	0,68
	Stayer	0,17	Class 1	0,85	1,00	0,00	1,00	0,00	1,00	0,00	1,00	0,00
			Class 2	0,15	0,00	1,00	0,00	1,00	0,00	1,00	0,00	1,00
B	Mover	0,41	Class 1	0,66	0,94	0,06	0,96	0,04	0,87	0,13	0,83	0,17
			Class 2	0,34	0,11	0,89	0,13	0,87	0,28	0,72	0,04	0,96
	Stayer	0,59	Class 1	1,00	1,00	0,00	1,00	0,00	1,00	0,00	1,00	0,00
			Class 2	0,00	0,00	1,00	0,00	1,00	0,00	1,00	0,00	1,00
F	Mover	0,37	Class 1	0,69	0,93	0,07	0,95	0,05	0,86	0,14	0,90	0,10
			Class 2	0,31	0,20	0,80	0,21	0,79	0,26	0,76	0,16	0,84
	Stayer	0,63	Class 1	0,92	1,00	0,00	1,00	0,00	1,00	0,00	1,00	0,00
			Class 2	0,08	0,00	1,00	0,00	1,00	0,00	1,00	0,00	1,00
IRL	Mover	0,67	Class 1	0,74	0,92	0,08	0,92	0,08	0,91	0,09	0,97	0,03
			Class 2	0,26	0,15	0,85	0,18	0,82	0,27	0,73	0,26	0,74
	Stayer	0,33	Class 1	0,89	1,00	0,00	1,00	0,00	1,00	0,00	1,00	0,00
			Class 2	0,11	0,00	1,00	0,00	1,00	0,00	1,00	0,00	1,00
I	Mover	0,52	Class 1	0,70	0,96	0,04	0,95	0,05	0,98	0,02	0,89	0,11
			Class 2	0,30	0,15	0,85	0,19	0,81	0,08	0,92	0,22	0,78
	Stayer	0,48	Class 1	0,95	1,00	0,00	1,00	0,00	1,00	0,00	1,00	0,00
			Class 2	0,05	0,00	1,00	0,00	1,00	0,00	1,00	0,00	1,00
EL	Mover	0,56	Class 1	0,69	0,91	0,09	0,90	0,10	0,93	0,07	0,90	0,10
			Class 2	0,31	0,16	0,84	0,11	0,89	0,25	0,75	0,12	0,88
	Stayer	0,44	Class 1	0,95	1,00	0,00	1,00	0,00	1,00	0,00	1,00	0,00
			Class 2	0,05	0,00	1,00	0,00	1,00	0,00	1,00	0,00	1,00
E	Mover	0,41	Class 1	0,83	0,92	0,08	0,95	0,05	0,84	0,16	0,71	0,29
			Class 2	0,17	0,84	0,16	0,11	0,89	0,45	0,55	0,00	1,00
	Stayer	0,59	Class 1	0,95	1,00	0,00	1,00	0,00	1,00	0,00	1,00	0,00
			Class 2	0,05	0,00	1,00	0,00	1,00	0,00	1,00	0,00	1,00
P	Mover	0,76	Class 1	0,74	1,00	0,00	0,95	0,05	0,97	0,03	0,97	0,03
			Class 2	0,26	0,15	0,85	0,15	0,85	0,25	0,75	0,28	0,72
	Stayer	0,24	Class 1	0,66	1,00	0,00	1,00	0,00	1,00	0,00	1,00	0,00
			Class 2	0,34	0,00	1,00	0,00	1,00	0,00	1,00	0,00	1,00
UK	Mover	0,51	Class 1	0,68	0,84	0,16	0,88	0,12	0,82	0,18	0,93	0,07
			Class 2	0,32	0,31	0,69	0,18	0,82	0,32	0,68	0,06	0,94
	Stayer	0,49	Class 1	0,93	1,00	0,00	1,00	0,00	1,00	0,00	1,00	0,00
			Class 2	0,07	0,00	1,00	0,00	1,00	0,00	1,00	0,00	1,00

more measurement error among those classified as poor,[19] except in the UK and Greece where the reliabilities are the same, and in Belgium and Spain where the reliabilities are lower among those classified as non-poor. It seems that the largest error in identifying the poor can be found in the Danish, Dutch and Portuguese tables: in Denmark we estimate that 38 per cent of those who are classified as poor in the latent variable are falsely observed to be non-poor: in the Dutch table the proportion of misclassified poor is 32 per cent and in the Portuguese 28 per cent. On the other hand, the proportion of the latent (i.e. true) non-poor who appear to be poor is only 2 per cent in Denmark, 1 per cent in the Netherlands and 3 per cent in Portugal. These results suggest that the measurement error in poverty dynamics is mainly associated in with a failure accurately to identify the poor, except in Belgium and in Spain.

The latent transition probabilities (τ) for the movers' chain show that rates of transition out of poverty are distinctively low in France, Ireland and the Southern-European countries. The transition out of poverty is relatively higher in the other countries, and is highest in the UK and Dutch tables. Transition rates into poverty are also highest in the Dutch and UK tables. Together these results suggest that the UK has the largest turnover in poverty among movers. Perhaps a clearer picture from which to draw comparisons can be seen if we calculate the overall latent transition rates that are presented in the Table 4.2.3, together with the observed transition rates. The overall latent transition rates are calculated as a weighted sum (using the π's as weights) of the transition rates of both movers and stayers. The overall latent transition rates show that the UK has the largest turnover in poverty among the entire population, not just among movers. Greece and Italy seem to be countries where the overall poverty fluidity is lowest. If we compared the latent rates to the observed transition rates, we can see how much measurement error increases poverty fluidity. In general, we can say that the error corrected probabilities of moving into poverty are slightly lower than the corresponding observed probabilities in every country. But it is interesting to find that the latent probabilities of moving out of poverty are much lower than the corresponding observed transition probabilities. Misclassifications seem to especially cause the flow from poverty to be over-estimated, while the over-estimation of flow into poverty is not that large. In other words, because of the failure to accurately identify the poor, much of what appears to be a move from poverty is, in fact, an error in classifying respondents. The measurement error in the financial poverty transition tables seems to be mainly due to false identification of a poor as a non-poor, just as the ρ's of the respondent probabilities indicated in the Table 4.2.2.

[19] We might expect that there are relatively more misclassifications among the poor, since the shape of income distribution shows that the vast majority of the poor are just below the financial poverty threshold, and this way misclassifications are more likely than among the non-poor majority of whom are not located near the poverty threshold.

TABLE 4.2.3: Corrected (latent) and observed transition probabilities for financial poverty dynamics

Country	Panel	State at t ↓	t+1=1995 Not poor	Poor	t+1=1996 Not poor	Poor	t+1=1997 Not poor	Poor
DK	Corrected	Not poor	1,00	0,00	0,98	0,02	0,89	0,11
		Poor	0,19	0,81	0,13	0,87	0,05	0,95
	Observed	Not poor	0,97	0,03	0,95	0,05	0,90	0,10
		Poor	0,56	0,44	0,52	0,48	0,42	0,58
NL	Corrected	Not poor	0,94	0,06	0,98	0,02	0,96	0,04
		Poor	0,23	0,77	0,20	0,80	0,19	0,81
	Observed	Not poor	0,93	0,07	0,96	0,04	0,95	0,05
		Poor	0,41	0,59	0,41	0,59	0,40	0,60
B	Corrected	Not poor	0,97	0,03	0,98	0,02	0,94	0,06
		Poor	0,05	0,95	0,05	0,95	0,12	0,88
	Observed	Not poor	0,92	0,08	0,95	0,05	0,92	0,08
		Poor	0,30	0,70	0,34	0,66	0,37	0,63
F	Corrected	Not poor	0,97	0,03	0,98	0,02	0,95	0,05
		Poor	0,07	0,93	0,08	0,92	0,09	0,91
	Observed	Not poor	0,95	0,05	0,95	0,05	0,93	0,07
		Poor	0,29	0,71	0,29	0,71	0,31	0,69
IRL	Corrected	Not poor	0,95	0,05	0,95	0,05	0,94	0,06
		Poor	0,10	0,90	0,12	0,88	0,18	0,82
	Observed	Not poor	0,92	0,08	0,91	0,09	0,92	0,08
		Poor	0,35	0,65	0,35	0,65	0,39	0,61
I	Corrected	Not poor	0,98	0,02	0,97	0,03	0,99	0,01
		Poor	0,08	0,92	0,10	0,90	0,04	0,96
	Observed	Not poor	0,92	0,08	0,92	0,08	0,92	0,08
		Poor	0,38	0,62	0,41	0,59	0,38	0,62
EL	Corrected	Not poor	0,95	0,05	0,94	0,06	0,96	0,04
		Poor	0,09	0,91	0,06	0,94	0,14	0,86
	Observed	Not poor	0,90	0,10	0,90	0,10	0,92	0,08
		Poor	0,33	0,67	0,27	0,73	0,36	0,64
E	Corrected	Not poor	0,97	0,03	0,98	0,02	0,94	0,06
		Poor	0,34	0,66	0,04	0,96	0,18	0,82
	Observed	Not poor	0,90	0,10	0,90	0,10	0,88	0,12
		Poor	0,54	0,46	0,43	0,57	0,43	0,57
P	Corrected	Not poor	1,00	0,00	0,96	0,04	0,98	0,02
		Poor	0,12	0,88	0,11	0,89	0,19	0,81
	Observed	Not poor	0,94	0,06	0,91	0,09	0,93	0,07
		Poor	0,30	0,70	0,28	0,72	0,34	0,66
UK	Corrected	Not poor	0,92	0,08	0,94	0,06	0,91	0,09
		Poor	0,16	0,84	0,09	0,91	0,16	0,84
	Observed	Not poor	0,91	0,09	0,92	0,08	0,90	0,10
		Poor	0,34	0,66	0,25	0,75	0,34	0,66

As was presented in the chapter three, we can calculate the true change and stability in the poverty transition tables using the error corrected parameter estimates of a Latent Markov model. We can break down the observed change and stability in the ten countries into true and error components using the parameter estimates presented in Table 4.2.2. In labelling the true change and stability, we followed the terminology of Langeheine and van de Pol (1990). The results are shown in Table 4.2.4, together with the observed proportion of stable cases (OBS) and the observed proportion of change (OBC). The observed proportion of stable cases and change are calculated from the observed frequencies presented in the Table 3.3.2. 'Perfect stability' is simply the proportion of the sample in the stayers' chain, which is the same as the chain proportion π in the Table 4.2.2. Perfect stability is measured without error, because we have assumed that the state occupied by the stayers is measured perfectly. The total proportion of stability TOS is then the number of movers remaining in their original state throughout the observation period, expressed as a proportion of the total sample. In other words, TOS indicates the true stability. The true observed stability TRS is then that part of true stability that is observed as stability. Change itself can be broken down in a similar way. True change, TOC, is 1.0 minus perfect stability and TOS. In other words, TOC, TOS and perfect stability sum always into one (or 100 per cent). TOC can be also partitioned into true observed change (TRC) and error. (OBC-TOC)/OBC ratio indicates that financial poverty mobility is over-estimated by 25 to 50 per cent in most of the countries if error is ignored.

The highest observed proportions of stable cases OBS can be found in the Netherlands where 81 per cent of the cases are observed to be stable, while the

TABLE 4.2.4: Estimated proportions of true stability and change and poverty rate in the financial poverty transition tables

	DK	NL	B	F	IRL	I	EL	E	P	UK
OBS	0.80	0.81	0.76	0.80	0.73	0.73	0.70	0.67	0.74	0.71
OBC	0.20	0.19	0.24	0.20	0.27	0.27	0.30	0.33	0.26	0.29
Perf.Stab.	0.20	0.17	0.59	0.63	0.33	0.48	0.44	0.59	0.24	0.49
TOS	0.65	0.66	0.29	0.25	0.47	0.42	0.39	0.25	0.62	0.27
TRS	0.55	0.61	0.16	0.16	0.37	0.25	0.25	0.07	0.49	0.21
error	0.09	0.06	0.13	0.09	0.10	0.18	0.14	0.18	0.14	0.07
TOC	0.16	0.17	0.12	0.12	0.20	0.10	0.17	0.15	0.14	0.23
TRC	0.08	0.08	0.08	0.07	0.11	0.05	0.11	0.07	0.07	0.18
error	0.07	0.08	0.05	0.05	0.09	0.05	0.06	0.09	0.07	0.06
Obs. rate	8,9	11,0	18,0	17,1	17,6	18,7	21,4	19,5	23,9	21,0
Latent rate	11,0	14,4	13,8	16,5	20,6	18,2	19,5	9,9	27,6	19,7

lowest observed proportion of stable cases is in Spain, at 67 per cent. The proportion of true stable cases that the Latent Mover-Stayer model estimates is equal to perfect stability plus total (i.e. true) stability TOS. When comparing the proportions of true stable cases with the observed proportions OBS, we can see that the observed data understates the true stability and overstates the change, as we would have expected. The true change (TOC) indicates that only 7 per cent experienced change in the Spanish panel, compared to the observed change (OBC) of 33 per cent. Correcting the over-estimation gives rise to a very striking change in the relative position of Spain, as well as Italy and Greece, in a ranking of poverty dynamics. Whereas in the observed data Southern-European countries appear to have the largest proportion of respondents who move between poverty and non-poverty (OBC), under the measurement model corrected for error, they have the lowest true change (TOC) proportion out of the ten countries. When observing the error corrected estimates, it seems that the UK has the highest financial poverty mobility; true change in the UK table is 18 per cent, though observed mobility is not the highest among the ten countries (29 %). Hence, the difference between the observed and true mobility rates is relatively small in the UK. Also when comparing observed poverty mobility rates and corrected rates, we can see that there is less country variation in the poverty mobility rates after removing the effect of measurement error. Especially in the Southern-European countries measurement error seems to play a significant role in the estimates of poverty mobility.

Errors affect not only comparisons of poverty mobility, but also comparisons of cross-sectional poverty rates. For example, comparing the observed poverty rate (in 1994) with the latent poverty rate in Table 4.2.4, it seems that the latent, or true, poverty rate shows somewhat less variation between countries than the observed poverty rate does. (The latent poverty rate is calculated from the π's and δ's in the Table 4.2.2.) Countries that have a low observed poverty rate tend to have somewhat higher latent poverty rate. For example, Denmark's latent poverty rate is 11 per cent compared to the observed nine per cent. The Netherlands has a latent poverty rate of 14 per cent compared to the observed 11 per cent. On the other hand, countries having higher observed poverty rates tend to have a lower latent rate than the observed haves, like the UK (observed 21 compared to the latent 20 per cent) and Italy (observed 19 compared to the latent 18 per cent). So it appears that, if we ignore error, we are not only likely to over-estimate poverty mobility, we might also under- or over-estimate cross-sectional poverty rates and over-estimate the country variation in poverty rates (see Breen & Moisio 2004).

The first two research hypotheses are not falsified when tested against the financial poverty panels: the population seems to be heterogeneous in their relation to poverty transition and poverty mobility is over-estimated if random error is ignored. Unfortunately, the indirect testing of the Individualisation thesis does not give as an unambiguous outcome. When observing the proportion of stayers in the financial poverty panels, we get evidence both for and against the Individualisation thesis: maturate welfare states tend to have a higher proportion of movers (e.g. Denmark and the Netherlands), but also some 'immature' welfare states have a high proportion of movers (e.g. Portugal). We now move to test the first two research hypotheses against the deprivation transition tables.

4.3 Dynamics of housing deprivation

4.3.1 Modelling deprivation transition with Latent Class and Markov models

We were able to account for the pattern of mobility in the financial poverty transition tables with a Mover-Stayer model, now we will test if we can explain the pattern of mobility in the housing deprivation tables using the same model. We have discovered from the descriptive figures that the indirect and the direct poverty measures draw a similar picture of poverty dynamics. How similar, we shall now find out. Table 4.3.1 presents the model fit diagnostics for the same twelve models that were tested in the previous section. Now these models are tested with the housing deprivation transition tables. Models are, once again, first tested with the stationarity constraints, then without constraints in the two-way transition probability matrixes (or in the latent conditional probabilities).

We start again with the Independence model that assumes no association between the measurement point *t* and *t*+n, so how well the model fits indicates how strong the associations are in the panel, or in this case, how deterministic deprivation is. The Independence model has 11 degrees of freedom and a poor fit with every country, as expected. Housing deprivation seems to be most deterministic in Portugal, where the Independence model produces the highest misclassification (Δ), 48.4 per cent of all cases (G^2 =17 934.2). Housing deprivation seems to be the least deterministic in Denmark, where the mismatch between the frequencies estimated by the Independence model and the observed frequencies is 13.8 per cent (G^2 =1 596.5). Comparison between the fit of the Independence model in the housing deprivation and financial poverty panels reveals an interesting finding. Housing deprivation seems to be *less* deterministic than financial poverty in every country (except in Portugal): misclassifications (Δ) produced by the Independence model are smaller in the housing deprivation tables than in the financial poverty transition tables. This is perhaps a surprising finding since one might have expected housing conditions to be more stable than the annual income flow.

TABLE 4.3.1: Markov and Latent Markov Models for housing deprivation dynamics

		DK		NL		B		F		IRL		I		EL		E		P		UK	
Model	df	G2	Delta	G2	Delta	G2	Delta	G2	Delta	G2	Delta	G2	Delta	G2	Delta	G2	Delta	G2	Delta	G2	Delta
(1) Independence	11	1 596,5	13,9	4 594,2	17,5	3 696	22,5	9 213,2	27,4	5 246,1	22,5	10815,0	23	9 918,6	33,7	9 863,6	28,0	17 934,2	48,4	2 741,8	16,7
(2) Q-Independ.	9	154,3	2,2	354,5	2,88	245,1	3,4	589,0	4,1	658,4	5,1	549,6	3,0	1147,6	7,4	858,9	4,7	1417,3	8,1	358,4	4,5
(3) Simple Markov	12	660,8	6,2	704,7	5,58	1 096,7	8,7	1 514,1	9,4	1 037,3	6,5	1 551,7	7,3	1 398,2	10,8	2 180,9	11,2	1 292,2	11,1	396,5	5,2
(4) Simple Markov*	8	586,4	6,1	638,6	4,87	941,6	8,5	1 498,6	9,1	814,4	6,7	1 499,3	7,2	1 212,3	10,5	2 070,4	11,0	1 220,9	11,1	280,1	4,3
(5) Markov 2 chain	8	209,6	2,5	77,7	1,52	99,6	2,1	103,8	1,7	206,8	2,5	217,3	2,2	429,8	5,1	406,2	3,6	293,3	4,3	63,7	1,5
(6) Mov-Stayer	10	211,1	2,49	194,4	2,42	405,3	4,5	278,1	3,0	435,8	3,6	252,1	2,4	511,7	5,3	528,6	3,74	295,4	4,2	159,1	3,1
(7) Mov-Stayer*	6	140,6	2,2	109,7	1,6	206,2	3,1	233,3	2,7	214,7	2,7	178,6	1,7	328,4	3,9	399,1	3,1	200,0	3,1	29,5	1,0
(8) LC	12	261,7	3,5	235,6	3,0	644,3	6,7	761,6	5,3	497,0	4,6	838,1	4,7	1 226,3	9,0	470,1	4,3	1 590,5	10,4	766,5	7,3
(9) LC*	6	70,1	0,1	121,8	1,5	291,0	3,2	264,5	2,7	175,4	1,9	363,3	2,4	267,0	3,6	251,8	2,6	1 226,3	8,5	66,8	1,5
(10) Lat. Markov	10	164,7	2,4	90,7	1,7	385,0	3,9	158,3	2,3	260,7	3,0	187,8	2,2	311,1	4,8	311,2	3,1	212,1	3,5	136,1	2,8
(11) Lat. Markov*	6	105,8	1,8	37,6	1,0	317,5	3,5	136,5	2,0	158,1	1,8	136,4	1,5	34,8	1,3	202,5	2,7	77,9	1,9	29,7	1,2
(12) Lat.Mov-Sta*	4	96,5	1,7	26,6	0,8	196,0	2,9	97,6	1,6	157,0	2,0	19,6	0,3	11,1	0,6	68,6	1,7	43,0	1,2	8,0	0,5

* The (latent) transition/conditional probabilities are not set equal between waves.

The Quasi-Independence model has 9 degrees of freedom and taking into account the non-mobile cases in the corner cells improves the fit of the model (compared to the Independence model) in every country. In some countries, like in Denmark (G^2=154.3; Δ=2.2) and in the Netherlands (G^2=354.5; Δ=2.9), the Quasi-Independence model can almost explain satisfactorily the associations observed in the housing deprivation transition tables. The biggest mismatch can be found once again in the Portuguese table, where the Quasi-Independence model misclassifies 8.1 per cent of all cases (G^2=1 417.3). Hence, after taking into account the two immobile groups in the corner cells of panel (never in deprivation and always in deprivation) mobility among those who change their deprivation status at least once seems to be surprisingly random in most of the countries.

The Simple Markov chain model, stationary or time-heterogeneous, seems to be unable to explain the associations in the deprivation transition tables. The stationary Simple Markov model has 12 degrees of freedom and fits best in the UK table, where the model misclassifies 5.2 per cent of all cases with the G^2 value of 396.5. The time-heterogeneous Simple Markov* chain model, where the two-way transition matrixes are allowed to vary from one wave to another, has 8 degrees of freedom and a slightly better fit to the data compared to the stationary Simple Markov model. The best fit can be found again in the UK table, where the time-heterogeneous Simple Markov* model misclassifies 4.3 per cent of all cases with the G^2 of 280.1. Allowing more than one transition trajectory in the population increases the fit of the model. However, we do not have enough degrees of freedom to estimate a Mixed Markov model without some constraints. So the fifth model, Markov 2 chain, is again a time-homogeneous two-chains Markov model where all the two-way transitions (in both chains) are restricted to be stationary. The model has 8 degrees of freedom and in the most of the countries the mismatch between the model and the data is around two per cent. The stationary two chain Markov model has the best fit with the Dutch (G^2=77.7) and with the UK (G^2=63.7) tables: misclassification is 1.5 per cent of all cases in both of the tables. The poorest fit can be found in the Greek table, where the model misclassifies 5.1 per cent of all cases with the G^2 value of 429.8. The substantial increase in the fit of the model when moving from Simple chain models to Mixed Markov models indicates that the population is heterogeneous in their relation to the transition of housing deprivation.

When constraining the two-way transition probabilities of the second chain to be an identity matrix, we turn (again) the two chains Mixed Markov model into the classic Mover-Stayer model. The time-homogeneous Mover-Stayer model has two degrees of freedom more than the time-homogeneous Markov 2 chain model, but the Mover-Stayer model has also a higher misclassification number compared to the Markov 2 chain model. When removing the stationarity restriction from the movers' chain, and thus letting the transition in the movers' chain be time-heterogeneous, we manage to increase the fit of the Mover-Stayer model. The time-heterogeneous Mover-Stayer* model has six degrees of freedom. The best fit can be found in the UK, where the model misclassifies only 1.0 per cent of the all cases with a G^2 value of 29.5. Misclassifications are somewhat higher in the other countries, but they remain below three per cent in most of the countries. The biggest mismatch can be found in the Greek table where the Mover-Stayer* model misclassifies 3.9 per cent of all cases (G^2=328.4). Therefore, it seems that the population can be divided into groups that have different housing deprivation dynamics, but we cannot find a Mixed Markov model that would have an adequate fit. An explanation for this might be again that a Mixed Markov model assumes that each observed variable measures perfectly the referent it is assumed to measure and because of this, a part of the mismatch between the model and the data is due to random error.

Before fitting measurement models that are able to separate error from the true change, we first must estimate the magnitude of error with a simple LC model with a dichotomous latent structure (in the same way as in the previous section). When a Latent Class model is fitted to a transition table, the model tests the extreme hypothesis that there is no real transition in the table, that all observed transition is error. The first LC model (model 8) has its latent conditional probabilities restricted to be stationary, meaning that the reliability matrixes are assumed to be identical at each measurement point. The LC model has 12 degrees of freedom and the model has the best fit with the Dutch table, where it misclassifies 3.0 per cent of all cases with the G^2 value of 235.6. The poorest fit can be found with the Portuguese table, where the LC model misclassifies 10.4 per cent of all cases with the G^2 value of 1 590.5. In the unconstrained LC* model (model 9) the reliability matrices are allowed to vary, in other words, we assume that the error varies between measurement points. Removing the equal reliability restriction takes four degrees of freedom, leaving six degrees of freedom to the LC* model. This loss of four degrees of freedom is compensated by the improved fit of the model in every country. The best fit is in the Danish table, where the LC* model misclassifies only 0.1 per cent of all cases with the G^2 value of 70.1. But in the other countries misclassifications are over two per cent, except in the Netherlands (1.5%), Ireland (1.9%) and in the UK (1.5%). The good fit of the unconstrained Latent Class model with the dichotomous latent structure indicates that a large part of the observed mobility in the housing deprivation tables might be explained as measurement error.

In the last three models (models 10 to 12) we again incorporate measurement error into the Markov model. The structural components of the Latent (Simple) Markov models are again direct counterparts to the stationary Simple Markov and time-heterogeneous Simple Markov* models. The structural component of the Latent Mover-Stayer model is identical with the (time-heterogeneous) Mover-Stayer model. We assume again that the error is the same at each measurement point, although this assumption is not necessarily valid. The difference between a Markov and a Latent Markov model is that the tested Markovian structure is now treated as a latent structure and observed measurements are related to this structure with probabilistic relationships, allowing a separate error for each manifest variable. The time-homogeneous (Simple) Latent Markov model has 10 degrees of freedom. The model has the best fit in the Dutch table with the G^2 value of 90.7 and the dissimilarity index value (Δ) of 1.7 per cent. But in most of the countries misclassifications are around three per cent or more. By allowing the latent transition probabilities to be time-heterogeneous (model 11) decreases the degrees of freedom to six, but the (Simple) time-heterogeneous Latent Markov* model also has much smaller misclassifications compared to the stationary Latent Markov model. The Latent Markov* model misclassifies only 1.0 per cent in the Dutch table with the G^2 value of 37.6 and the rest of the countries' misclassifications are below two per cent, except in the Belgium (3.5%), French (2.0%) and Spanish (2.7%) tables. If we compare the misclassifications of the Simple Markov* model to those of the (Simple) Latent Markov* model, we can see that the latter produces much smaller misclassifications than the former. This indicates that measurement error plays a significant role in the observed deprivation mobility.

Misclassifications between the time-heterogeneous (Simple) Latent Markov* model and the data are around two per cent in the most of the countries, so it seems that incorporating error in a (Simple) Markov model is not enough. We might consider abandoning the assumption that the whole population follows the same poverty trajectory. So we turn again towards the Latent Mixed Markov model that was used in the previous section. The time-heterogeneous (partially) Latent Mover-Stayer model* assumes that there are two poverty trajectories in the population, i.e. for movers and stayers. The model assumes a constant error when estimating the movers' chain and no error when estimating the stayers' chain. The Latent Mover-Stayer model has 4 degrees of freedom and it has a very good fit with the Dutch, Italian, Greek and the UK tables, where the model misclassifies less than one per cent of the cases. In the rest of the countries the fit is also relatively good; misclassifications are two per cent or less, except in Belgium where the misclassification is 2.9 per cent of all cases with the G^2 value of 196.0. There are statistically significant differences at the .05 level between the estimated and observed frequencies in every country, as the G^2 values indicate. However, taking into account again the large sample sizes and that we are modelling 16-cell transition tables, this degree of fit seems adequate. We can therefore justifiably conclude that housing deprivation dynamics also seem to follow a process that can be described by the time-heterogeneous (Latent) Mover-Stayer model that allows for error in the measurement of the movers' states.[20]

[20] We again tested a model that allows the stayers to be measured with separate error. However, releasing stayers' reliabilities did not improve the model fit, so we chose the more parsimonious model.

4.3.2 Error corrected estimates for deprivation dynamics

Table 4.3.2 presents the estimated parameter coefficients for the final time-heterogeneous Latent Mover-Stayer model, fitted to the housing deprivation transition tables. The first column again presents the π coefficients that indicate the proportions of population belonging either to the movers' or stayers' chain. There seems to be a bigger variance between countries in the proportion of movers and stayers in the deprivation tables than were in the financial poverty transition tables. In some countries the proportion of stayers is very small, as in Denmark and in France, 3 and 6 per cent respectively. We can calculate again the proportion of the population that can be expected to never or always be in deprivation by multiplying the chain proportion π with the initial probability δ. The smallest proportion of population always in deprivation is in the Netherlands, where the model estimates that the proportion is zero per cent, as can be seen in the Table 4.5. In fact, the proportion of population always deprived is almost zero everywhere except in Portugal, where 5.9 per cent of the population is estimated to be stably deprived, and in Belgium and France, where the figure is 1.9 per cent. On the other hand, the proportion of the population that is expected never to be deprived is the highest in Belgium and in the Netherlands, at 63.7 and 59.3 per cent. An interesting observation is that there seems to be relatively more people estimated to be in constant financial poverty than in constant housing deprivation (Belgium being the only exception). One might have expected that an incidence of housing deprivation, once started, would be more prone to turn into a long-term situation than an incidence of financial poverty.

The matrix of response probabilities (ρ's) indicates the reliability of the measure of housing deprivation. The modal response probabilities on the diagonal cells can be treated as reliabilities and probabilities on off-diagonal cells as error. We can see that there seems to be more measurement error among those classified as deprived (except in Spain and Italy where the reliabilities are roughly the same for the deprived and non-deprived): error in the housing deprivation measure seems to be caused mainly by the misclassifications where a deprived case is falsely classified as non-deprived. This is a parallel finding to one that was made when the reliability of financial poverty measure was studied. The weakest reliability in identifying the deprived can be found in the Danish and French tables. In Denmark, the model estimates that almost half (49%) of those who are classified as deprived in the latent variable (i.e. are truly deprived) are classified as non-deprived by the manifest deprivation measure. In the French table, the proportion of those truly deprived misclassified as non-deprived is 36 per cent. The truly non-deprived cases appear to be identified with much less error than the truly deprived cases. Only a small fraction of misclassifications are due to a truly non-deprived case being falsely classified as deprived. These results suggest that measurement error in housing deprivation dynamics is mainly associated with a failure to accurately to identify

TABLE 4.3.2: Estimated parameter values for Partially Latent Movers-Stayers Model for housing deprivation

Country	Chain proportion Chain	π	Initial proportion Class	δ	Latent Transition Probabilities τ t to t+1						Response probabilities	
					Class 1	Class 2	Class 1	Class 2	Class 1	Class 2	non-deprived	deprived
DK	Mover	0,97	Class 1	0,84	1,00	0,00	1,00	0,00	0,98	0,02	0,99	0,01
			Class 2	0,16	0,23	0,77	0,00	1,00	0,55	0,45	0,49	0,51
	Stayer	0,03	Class 1	0,86	1,00	0,00	1,00	0,00	1,00	0,00	1,00	0,00
			Class 2	0,14	0,00	1,00	0,00	1,00	0,00	1,00	0,00	1,00
NL	Mover	0,41	Class 1	0,78	0,91	0,09	0,96	0,04	1,00	0,00	0,92	0,08
			Class 2	0,22	0,30	0,70	0,28	0,72	0,13	0,87	0,19	0,81
	Stayer	0,59	Class 1	1,00	1,00	0,00	1,00	0,00	1,00	0,00	1,00	0,00
			Class 2	0,00	0,00	1,00	0,00	1,00	0,00	1,00	0,00	1,00
B	Mover	0,34	Class 1	0,62	0,74	0,26	1,00	0,00	0,89	0,11	0,86	0,14
			Class 2	0,38	0,39	0,61	0,66	0,34	0,45	0,55	0,23	0,77
	Stayer	0,66	Class 1	0,97	1,00	0,00	1,00	0,00	1,00	0,00	1,00	0,00
			Class 2	0,03	0,00	1,00	0,00	1,00	0,00	1,00	0,00	1,00
F	Mover	0,94	Class 1	0,72	0,99	0,01	0,99	0,02	0,96	0,04	0,98	0,02
			Class 2	0,28	0,21	0,79	0,21	0,79	0,19	0,81	0,36	0,64
	Stayer	0,06	Class 1	0,69	1,00	0,00	1,00	0,00	1,00	0,00	1,00	0,00
			Class 2	0,31	0,00	1,00	0,00	1,00	0,00	1,00	0,00	1,00
IRL	Mover	0,55	Class 1	0,72	0,99	0,01	0,93	0,07	1,00	0,00	0,95	0,05
			Class 2	0,28	0,36	0,64	0,15	0,85	0,07	0,93	0,23	0,77
	Stayer	0,45	Class 1	1,00	1,00	0,00	1,00	0,00	1,00	0,00	1,00	0,00
			Class 2	0,00	0,00	1,00	0,00	1,00	0,00	1,00	0,00	1,00
I	Mover	0,44	Class 1	0,70	0,94	0,06	0,97	0,03	1,00	0,00	0,89	0,11
			Class 2	0,30	0,41	0,59	0,23	0,77	0,22	0,78	0,13	0,87
	Stayer	0,56	Class 1	0,98	1,00	0,00	1,00	0,00	1,00	0,00	1,00	0,00
			Class 2	0,02	0,00	1,00	0,00	1,00	0,00	1,00	0,00	1,00
EL	Mover	0,80	Class 1	0,58	0,93	0,07	0,96	0,04	0,97	0,03	0,92	0,08
			Class 2	0,42	0,37	0,63	0,16	0,84	0,09	0,91	0,15	0,85
	Stayer	0,21	Class 1	0,99	1,00	0,00	1,00	0,00	1,00	0,00	1,00	0,00
			Class 2	0,01	0,00	1,00	0,00	1,00	0,00	1,00	0,00	1,00
E	Mover	0,50	Class 1	0,67	0,85	0,15	0,98	0,02	0,95	0,05	0,83	0,17
			Class 2	0,33	0,44	0,56	0,10	0,90	0,08	0,92	0,18	0,82
	Stayer	0,50	Class 1	1,00	1,00	0,00	1,00	0,00	1,00	0,00	1,00	0,00
			Class 2	0,00	0,00	1,00	0,00	1,00	0,00	1,00	0,00	1,00
P	Mover	0,76	Class 1	0,48	0,87	0,13	0,87	0,13	0,94	0,06	0,94	0,06
			Class 2	0,52	0,15	0,85	0,16	0,84	0,08	0,92	0,10	0,90
	Stayer	0,24	Class 1	0,75	1,00	0,00	1,00	0,00	1,00	0,00	1,00	0,00
			Class 2	0,25	0,00	1,00	0,00	1,00	0,00	1,00	0,00	1,00
UK	Mover	0,52	Class 1	0,62	0,90	0,10	0,96	0,04	0,95	0,05	0,98	0,02
			Class 2	0,38	0,62	0,38	0,30	0,70	0,39	0,61	0,25	0,75
	Stayer	0,48	Class 1	0,98	1,00	0,00	1,00	0,00	1,00	0,00	1,00	0,00
			Class 2	0,02	0,00	1,00	0,00	1,00	0,00	1,00	0,00	1,00

the deprived (except in Spain and Italy). Also it appears that the housing deprivation indicator has a lower reliability than the financial poverty measure. This does not support the often-presented thesis that direct poverty measures would be more reliable than indirect poverty measures (see Ringen 1988).

Parameter estimates describing the latent transition probabilities in Table 4.3.2 are quite difficult to interpret since they present the rate of transitions separately for movers' and stayers' chains. For this reason, we have again calculated the overall latent, or true, transition rates that are presented in the Table 4.3.3. The overall

TABLE 4.3.3: Corrected (latent) and observed transition probabilities for deprivation dynamics

Country	Panel	State at t ↓	t+1=1995 Not Depr	t+1=1995 Depr	t+1=1996 Not Depr	t+1=1996 Depr	t+1=1997 Not Depr	t+1=1997 Depr
DK	Corrected	Not Depr	1,00	0,00	1,00	0,00	0,98	0,02
		Depr	0,22	0,78	0,00	1,00	0,54	0,46
	Observed	Not Depr	0,96	0,04	0,94	0,06	0,97	0,03
		Depr	0,70	0,30	0,55	0,45	0,72	0,28
NL	Corrected	Not Depr	0,96	0,04	0,99	0,01	1,00	0,00
		Depr	0,12	0,88	0,11	0,89	0,05	0,95
	Observed	Not Depr	0,94	0,06	0,96	0,04	0,96	0,04
		Depr	0,53	0,47	0,53	0,47	0,46	0,54
B	Corrected	Not Depr	0,91	0,09	1,00	0,00	0,96	0,04
		Depr	0,13	0,87	0,23	0,77	0,15	0,85
	Observed	Not Depr	0,91	0,09	0,96	0,04	0,93	0,07
		Depr	0,46	0,54	0,61	0,39	0,53	0,47
F	Corrected	Not Depr	1,00	0,00	0,99	0,01	0,97	0,03
		Depr	0,20	0,80	0,20	0,80	0,17	0,83
	Observed	Not Depr	0,92	0,08	0,93	0,07	0,92	0,08
		Depr	0,48	0,52	0,48	0,52	0,45	0,55
IRL	Corrected	Not Depr	0,99	0,01	0,96	0,04	1,00	0,00
		Depr	0,20	0,80	0,08	0,92	0,04	0,96
	Observed	Not Depr	0,95	0,05	0,93	0,07	0,96	0,04
		Depr	0,61	0,39	0,45	0,55	0,37	0,63
I	Corrected	Not Depr	0,98	0,02	0,99	0,01	1,00	0,00
		Depr	0,18	0,82	0,10	0,90	0,09	0,91
	Observed	Not Depr	0,94	0,06	0,94	0,06	0,95	0,05
		Depr	0,51	0,49	0,45	0,55	0,46	0,54
EL	Corrected	Not Depr	0,94	0,06	0,97	0,03	0,98	0,02
		Depr	0,30	0,70	0,12	0,88	0,07	0,93
	Observed	Not Depr	0,87	0,13	0,89	0,11	0,90	0,10
		Depr	0,49	0,51	0,38	0,62	0,35	0,65
E	Corrected	Not Depr	0,92	0,08	0,99	0,01	0,97	0,03
		Depr	0,22	0,78	0,05	0,95	0,04	0,96
	Observed	Not Depr	0,89	0,11	0,90	0,10	0,90	0,10
		Depr	0,54	0,46	0,43	0,57	0,44	0,56
P	Corrected	Not Depr	0,90	0,10	0,90	0,10	0,96	0,04
		Depr	0,12	0,88	0,12	0,88	0,06	0,94
	Observed	Not Depr	0,84	0,16	0,85	0,15	0,87	0,13
		Depr	0,22	0,78	0,24	0,76	0,19	0,81
UK	Corrected	Not Depr	0,95	0,05	0,98	0,02	0,98	0,02
		Depr	0,33	0,67	0,16	0,84	0,20	0,80
	Observed	Not Depr	0,95	0,05	0,96	0,04	0,96	0,04
		Depr	0,69	0,31	0,47	0,53	0,52	0,48

latent transition rates are calculated by multiplying the π by the τ in the movers' and stayers' chains and then summing up the two products. The observed transition rates are presented below the overall latent transition rates. According to the latent transition probabilities, overall (true) fluidity seems to be highest in the UK table, while the lowest (true) fluidity seems to be in the Dutch table. When comparing the error corrected (latent) transition probabilities to the observed transition probabilities, we can see that measurement error increases especially the transition probabilities out of deprivation. In other words, errors lead us to over-estimate the flow from out of deprivation. Error seems to play a much smaller part in the observed transition rates into deprivation: the difference between the true inflow rate and the observed inflow rate is usually much smaller than the difference between the true and observed outflow rates. It seems that since the state of deprivation is poorly identified, much of what appears to be the change from deprivation is, in fact, error in classifying respondents. Measurement error in the deprivation transition tables seems to be most often a failure to identify a truly deprived case as deprived. So not only the dynamics are similar with the direct and indirect measures, but also measurement error seems to be located in the same place with the direct and indirect poverty measures.

In Table 4.3.4 we have estimated true change (TOC) and true stability (TOS) in the transition tables using the parameter estimates of the Latent Mover-Stayer model. Observed stability (OBS) and observed change (OBC) are calculated for each country using the observed frequencies. The highest observed change can be found in the Greek table, where 41 per cent of the cases are observed to have changed deprivation status at least once. The lowest observed change rates are in the Danish and Dutch tables, at 18 per cent. However, the (OBC-TOC)/OBC ratio indicates that mobility in the deprivation transition tables is over-estimated by 30 to 50 per cent, except in the UK where mobility is over-estimated only by 4 per cent. Hence, the observed mobility rate overstates the change. When we remove error from the observed change and estimate true change (TOC), we can see that not only is true change smaller than observed change, but that the TOC has a smaller variation between countries than the observed change. It seems that especially in the Southern-European countries measurement error causes mobility to be over-estimated in the deprivation transition tables. For example, the TOC indicates that only 23 per cent have experienced mobility in the Greek table, compared to the observed change of 41 per cent. However, the countries' relative positions on a ranking of deprivation dynamics do not change as dramatically when error is removed as it did with financial poverty dynamics. Countries that have higher observed deprivation mobility tend to also have higher observed mobility.

Studying the error corrected parameter estimates we can see that error also affects the comparisons of cross-sectional deprivation rates. We can again estimate the true cross-sectional deprivation rates from the πs and δs of the Latent Mover-Stayer model. Comparing the observed deprivation rate (in 1994) with the error corrected deprivation rates in Table 4.3.4, we see that the error-corrected deprivation rate shows somewhat less variation between countries than the observed rate does. Countries that have a low observed deprivation rate tend to have a higher latent

TABLE 4.3.4: Estimated proportions of true stability and change and deprivation rate in the housing deprivation transition tables

	DK	NL	B	F	IRL	I	EL	E	P	UK
OBS	0.82	0.82	0.76	0.71	0.78	0.77	0.59	0.67	0.62	0.77
OBC	0.18	0.18	0.24	0.29	0.22	0.23	0.41	0.33	0.38	0.23
Perf.Stab.	0.03	0.59	0.66	0.06	0.45	0.56	0.21	0.50	0.24	0.48
TOS	0.85	0.32	0.16	0.77	0.44	0.33	0.56	0.34	0.52	0.30
TRS	0.76	0.22	0.08	0.61	0.32	0.20	0.37	0.16	0.37	0.26
error	0.09	0.10	0.07	0.16	0.12	0.12	0.19	0.18	0.15	0.05
TOC	0.12	0.09	0.19	0.17	0.11	0.11	0.23	0.16	0.24	0.22
TRC	0.03	0.05	0.09	0.08	0.06	0.07	0.15	0.07	0.17	0.13
error	0.08	0.04	0.10	0.09	0.04	0.04	0.09	0.08	0.07	0.08
Obs. rate	9,9	9,6	14,8	20,0	14,0	15,6	32,3	19,3	43,6	16,3
Latent rate	16,1	8,9	14,8	28,0	15,5	13,8	33,6	16,3	45,5	20,5

deprivation rate. For example, Denmark has a latent rate of 16 per cent compared to an observed rate of 10 per cent. On the other hand, countries having a higher observed deprivation rate tend to have a lower latent deprivation rate. However, this association is not that clear. It is clear that measurement error also affects the cross-sectional deprivation rate, not just the estimates of mobility.

We have thus drawn similar conclusions with deprivation dynamics as we did in the previous section with financial poverty dynamics. Therefore, the answer to the two research questions is once again 'yes' in both cases. Firstly, the population seems to be heterogeneous and the two groups in the population, movers and stayers, follow their own transition trajectories. Secondly, random error causes mobility in the deprivation transition table to be over-estimated by 30 to 50 per cent in most of the countries, if error is not corrected. Hence, the over-estimation of mobility seems to be an even bigger problem with the direct poverty measure than with the indirect in many countries (mobility is over-estimated only by 25 to 50 per cent in the financial poverty transition tables). In several countries, the estimates of deprivation mobility show higher over-estimation than the estimates of financial poverty mobility. We also noted that there is often a higher proportion of movers in countries with a more extensive welfare state, for example in Denmark at 97 per cent. This observation is congruent with the individualisation thesis, which suggests (indirectly) that poverty is less deterministic in countries that have a 'maturated' welfare state. However, the proportion of movers is low in the Netherlands (41%), which is seen as having an extensive welfare state. Therefore, the evidence that the proportion of movers can give to the individualisation thesis is not unambiguous. We now move to model the dynamics of our third and last poverty indicator, the subjective deprivation classification.

4.4 Dynamics of subjective deprivation

4.4.1 Modelling subjective deprivation transition with Latent Class and Markov models

If there are differences between our three poverty measures, we might expect that the differences would be concentrated between the two previous objective measures and the subjective measure. Our subjective deprivation measure is based on the question posed to the head of the household 'Are you able to make ends meet' (see Table 3.3.1). The same set of twelve models that are used in the previous sections is now fitted to the subjective deprivation transition tables. Models are, again, fitted separately to the each national transition table. The model fit diagnostics of these twelve models are presented in the Table 4.4.1. We start again with saturated structural models (models one to seven) that assume no error in the measurement, and then try to improve the fit of the model by allowing for error in the model (models eight to twelve).

The Independence model where all transition parameters are omitted from the model again gives us a good starting point by indicating how deterministic subjective deprivation is. The Independence model has 11 degrees of freedom and a poor fit in every country, as expected. Subjective deprivation seems to be the most deterministic in Portugal, since the Independence model has the highest misclassification in the Portuguese table, 40.6 per cent of the cases with the G^2 value of 12 850.4. The least deterministic subjective deprivation seems to be in the UK, where the Independence model misclassifies 18.6 per cent of the cases with the G^2 value of 4 453.5. It seems quite clear that an incidence of subjective deprivation at time *t* has an association with an incidence of subjective deprivation at time *t+n*. The Quasi-independence model tests the assumption that the movers move randomly by releasing the two corner cells in the transition table to be estimated freely (see Appendix A). The Quasi-independence model has a much better fit in every country than the independence model. In fact, in several countries, the Quasi-independence model misclassifies only around three per cent of the all cases. The smallest misclassification (Δ) can be found in the UK table, where the Quasi-independence model misclassifies 2.5 per cent of all cases with the G^2 value of 217.7. The poorest fit can be found in the Greek table, where the model misclassifies 8.3 per cent of all cases with the G^2 value of 1 005.7. The relatively good fit of the Quasi-independence model in many countries suggests that there is a similar structure behind subjective deprivation transitions as behind the transitions of financial poverty and housing deprivation. The structure of subjective deprivation dynamics seems to mean that there are two immobile groups, those who stay in deprivation or stay out of deprivation, and between these two groups there is a group of movers.

However, before moving on to models that assume a heterogeneous population, we can test a single chain Markov model to explain associations in the subjective deprivation transition tables. The time-homogeneous Simple Markov model has 12 degrees of freedom, but it seems that the model is unable to explain subjective deprivation dynamics in any country. The best fit can be found in the Danish and the UK tables, where the time-homogeneous Simple Markov model misclassifies 6.5 per cent of the all cases. Removing the stationarity restriction from the two-way transition probabilities takes four degrees of freedom and improves the fit only little. The time-heterogeneous Simple Markov* model has the best fit in the UK table, where the model misclassifies 5.9 per cent of the cases with the G^2 value of 738.9. So the transition of subjective deprivation seems not to follow a simple Markovian process, even when we let the two-way transition probabilities vary between measurement points. A possible explanation for the poor fit might be, as we expect, that there is more than one deprivation trajectory in the population, not only one like the Simple Markov model assumes.

Increasing the number of chains in the Markov model and turning the model into a Mixed Markov model improves the fit of the model. Again, we do not have enough degrees of freedom to estimate a Mixed Markov model without some constraints. So the Markov 2 chain model is time-homogeneous and has its two-way transition probabilities set to be stationary. The model has 8 degrees of freedom and it estimates less than two per cent of the cases incorrectly in the Dutch (G^2=55.5; Δ=1.9) and in the Italian (G^2=134.2; Δ=1.7) tables. In the rest of the countries, however, the misclassifications are higher. Restricting the two-way transition probability matrixes in the second chain to be an identity matrix releases two degrees of freedom, so the Mover-Stayer model has 10 degrees of freedom. However, the time-homogeneous Mover-Stayer model does not have a particularly good fit. A likely explanation for this might be that the transition probabilities in the movers' chain are assumed to be time-homogeneous. The Mover-Stayer* model removes the stationary constraint from the movers' two-way transition probabilities and this takes 4 degrees of freedom, leaving 6 degrees of freedom in use. The time-heterogeneous Mover-Stayer* model has a reasonably good fit: in many countries the misclassification is less than two per cent. The best fit can be found with the UK table, where the model misclassifies 1.5 per cent of the cases with the G^2 value of 69.3. However, the misclassifications are higher in other countries, indicating that allowing the population to be heterogeneous is not enough to gain a Markov chain model with an acceptable fit with the data.

TABLE 4.4.1: Markov and Latent Markov Models for subjective deprivation dynamics

		DK		NL		B		F		IRL		I		EL		E		P		UK	
Model	df	G2	Delta	G2	Delta	G2	Delta	G2	Delta	G2	Delta	G2	Delta	G2	Delta	G2	Delta	G2	Delta	G2	Delta
(1) Independence	11	3 162,3	20,6	6735,0	24,6	4 711,4	26,2	8288,0	27,6	7 552,8	36,7	11 586,2	29,8	10 788,1	37,7	10 987,1	32,6	12 850,4	40,6	4453,5	18,6
(2) Q-Independ.	9	248,6	3,5	256,6	2,9	232,0	3,4	337,8	3,6	477,7	5,8	749,9	4,7	1 005,7	8,3	643,0	5,9	1 301,1	8,0	217,7	2,5
(3) Simple Markov	12	437,5	6,5	1 128,3	8,1	679,2	7,8	1 746,1	10,8	1 382,3	14,1	1 777,6	10,1	1 588,7	13,7	3 076,6	18,2	1 796,2	13,7	791,1	6,5
(4) Simple Markov*	8	363,1	6,1	1 166,3	8,0	652,3	7,4	1 733,2	10,7	1 267,9	14,3	1 707,6	10,0	1 319,7	14,1	2 899,5	17,5	1 614,9	13,9	738,9	5,9
(5) Markov 2 chain	8	92,7	2,5	55,5	1,3	108,5	2,2	177,5	2,6	287,2	4,4	134,2	1,7	438,8	5,9	624,5	5,3	565,1	6,4	130,3	2,3
(6) Mov-Stayer	10	112,8	2,8	135,0	2,1	111,1	2,2	177,5	2,6	289,8	4,4	312,6	3,0	464,4	6,0	642,7	5,78	634,5	6,7	149,0	2,4
(7) Mov-Stayer*	6	63,2	1,7	95,8	1,9	82,7	1,9	162,0	2,4	190,8	3,7	233,6	2,8	141,3	3,1	445,2	5,0	414,8	4,5	69,3	1,5
(8) LC	12	432	6,1	168,5	2,8	362,3	4,4	235,7	3,4	473,0	7,0	568,8	4,1	929,1	9,1	937,6	7,6	983,7	9,5	273,7	3,5
(9) LC*	6	177,9	3,1	90,6	1,8	303,4	3,6	144,7	2,3	202,7	4,0	323,0	3,0	422,7	6,7	665,7	5,8	479,7	6,4	95,3	1,5
(10) Lat. Markov	10	211,6	4,2	97,1	2,0	161,0	3,2	114,8	2,2	252,0	4,2	126,2	1,9	392,1	6,0	785,2	5,9	425,5	5,3	73,9	1,7
(11) Lat. Markov*	6	133,5	3,3	71,4	1,4	98,2	2,3	99,7	2,0	164,9	3,0	96,2	1,4	200,2	4,3	640,0	5,2	201,2	3,5	47,8	1,2
(12) Lat.Mov-Sta*	4	49,9	1,6	15,7	0,6	38,4	1,4	36,7	1,2	58,7	1,7	25,7	0,8	81,8	2,2	312,3	3,5	101,4	2,2	19,3	0,8

* The (latent) transition/conditional probabilities are not set equal between waves.

We expect that measurement error causes a mismatch between the model and the data, as has been the case with the two previous measures. By fitting a Latent Class model with two latent classes we can again gain a quantitative description on the amount of error in the subjective deprivation transition tables. The LC model, when fitted to a transition table, tests the extreme hypothesis that all observed change is error. The LC model has 12 degrees of freedom when the latent conditional probabilities are set to be stationary, i.e. when error is assumed to be constant from the measurement point to the next. The LC model has the best fit with the Dutch table where the model misclassifies 2.8 per cent of all cases with the G^2 value of 168.5. In the rest of the countries the mismatch is much higher. In the unconstrained LC* model, the latent conditional probabilities are allowed to vary, i.e. the model assumes that reliabilities vary between measurement points, and this takes 6 degrees of freedom. The unconstrained LC* has a better fit with the data than the LC model. The best fit can be found again in the UK table where the model misclassifies 1.5 per cent of all cases with the G^2 value of 95.3. Again the LC* model has a surprisingly good fit with every country, when the extreme assumption that the model makes about the nature of transition, i.e. that all transition is error, is kept in mind. This indicates that a large part of the subjective deprivation mobility we have just modelled with Markov models is just random error.

We tackle this error again by using measurement models that allow each manifest indicator to measure subjective deprivation imperfectly. The time-heterogeneous (Simple) Latent Markov* model seems to have a better fit to the data than its stationary counterpart, the time-homogeneous (Simple) Latent Markov model. This is not a surprise, since we have already learnt that the two-way transition probabilities are not constant through time. The time-heterogeneous Latent Markov* model has six degrees of freedom and the model has the best fit with the UK table, where the dissimilarity index indicates that 1.2 per cent of the cases is misclassified with the G^2 value of 47.8. When comparing the fit of the Latent Markov* model to the fit of the Simple Markov* model (which is the direct counterpart to the structural sub-model in the Latent Markov* model), we can see that in most of the countries the likelihood ratios and misclassifications produced by the Latent Markov* model are only a fraction of what the Simple Markov* model produces. This indicates that if we use models that assume a saturated structural model (i.e. no mismatch between the model and the data is allowed), then error will be mistaken for a substantive effect. This may lead easily to false conclusions about the structure of associations in the data.

The (Simple) Latent Markov model assumes a homogeneous population and this is the most likely reason for the remaining mismatch between the model and the data. So the final model, time-heterogeneous (partially) Latent Mover-Stayer model allows for error and assumes that the population consist of two groups, movers and stayers, that both follow their own transition trajectory. The Latent

Mover-Stayer seems to describe the dynamics of subjective deprivation quite well in every country, except in Greece, Spain and Portugal. The model has four degrees of freedom left and it misclassifies less than one per cent of all the cases in the Netherlands (G^2=15.7), in Italy (G^2=25.7) and in the UK (G^2=19.3). Only in Greece, Spain and Portugal are the misclassifications (Δ) over two per cent of all the cases. Hence, it seems that we can model the subjective deprivation transition with the same Latent Mover-Stayer model than we used to model the transitions of financial poverty and housing deprivation. Also, as was the case with the two objective poverty measures, allowing the stayers' chain to contain measurement error does not improve the model fit. Even though there are statistically significant differences between the observed and estimated models in a every country (at 0.05 level), we can be satisfied with the model fit when baring in mind again that we are modelling transition tables with large Ns.

4.4.2 Error corrected estimates for subjective deprivation dynamics

The estimated parameter values of the time-heterogeneous Latent Mover-Stayer model are presented in the Table 4.4.2. There is a large country variation in the proportion of movers (and correspondingly in the proportion of stayers) as the chain proportion π indicates. Unlike with the previous two objective poverty measures, the largest movers' groups can be now found in the Southern-European countries where, the clear majority of the population is estimated to be movers. In Spain and in Portugal, the proportion of movers is especially high: at 93 and 90 per cent. However, when observing the initial probabilities that indicate how many of the movers (or stayers) are classified as (subjectively) deprived at the first measurement point, we can see that there are also relatively more deprived people among the movers in the Southern-European countries. By multiplying the chain proportion π with the initial probability δ, we can estimate the proportion of population that will never be in deprivation, and also the proportion of population that live in constant subjective deprivation. The highest proportion of population that is always in subjective deprivation can be found in Greece, at 14.9 per cent, and the proportion of those in constant subjective deprivation is also high in Portugal (10.4%) and in Spain (7.3%). The highest proportions of people never expected to experience deprivation can be found in the Netherlands (59.6%), Denmark (50.9%) and in the UK (49.1%), where roughly a half of the population is estimated to be in no risk of subjective deprivation. The proportion of stayers is low in Spain and Portugal, but the fraction of stayers that are deprived is high: in Spain 98 per cent of the stayers are estimated to be deprived and in Portugal the full 100 per cent. On the other hand, in Ireland and in Italy the model estimates that there are no stable deprived at all.

TABLE 4.4.2: Estimated Parameter values for Partially Latent Movers-Stayers Model for subjective deprivation

Country	Chain proportion Chain	π	Initial proportion Class	δ	Latent Transition Probabilities τ t to t+1						Response probabilities	
					Class 1	Class 2	Class 1	Class 2	Class 1	Class 2	non-deprived	deprived
DK	Mover	0,46	Class 1	0,75	0,94	0,06	0,93	0,07	0,93	0,07	0,94	0,06
			Class 2	0,25	0,68	0,32	0,29	0,71	0,53	0,47	0,06	0,94
	Stayer	0,54	Class 1	0,95	1,00	0,00	1,00	0,00	1,00	0,00	1,00	0,00
			Class 2	0,05	0,00	1,00	0,00	1,00	0,00	1,00	0,00	1,00
NL	Mover	0,39	Class 1	0,69	0,94	0,06	0,95	0,05	0,96	0,04	0,89	0,11
			Class 2	0,31	0,29	0,71	0,03	0,97	0,24	0,76	0,24	0,76
	Stayer	0,61	Class 1	0,98	1,00	0,00	1,00	0,00	1,00	0,00	1,00	0,00
			Class 2	0,02	0,00	1,00	0,00	1,00	0,00	1,00	0,00	1,00
B	Mover	0,91	Class 1	0,83	0,95	0,05	0,97	0,03	0,96	0,04	0,98	0,02
			Class 2	0,17	0,06	0,94	0,31	0,69	0,20	0,80	0,36	0,64
	Stayer	0,09	Class 1	0,65	1,00	0,00	1,00	0,00	1,00	0,00	1,00	0,00
			Class 2	0,35	0,00	1,00	0,00	1,00	0,00	1,00	0,00	1,00
F	Mover	0,80	Class 1	0,70	0,94	0,06	0,96	0,04	0,98	0,02	0,96	0,04
			Class 2	0,30	0,14	0,86	0,08	0,92	0,14	0,86	0,40	0,60
	Stayer	0,20	Class 1	0,90	1,00	0,00	1,00	0,00	1,00	0,00	1,00	0,00
			Class 2	0,10	0,00	1,00	0,00	1,00	0,00	1,00	0,00	1,00
IRL	Mover	0,64	Class 1	0,55	0,97	0,03	0,91	0,09	0,97	0,03	0,81	0,19
			Class 2	0,45	0,29	0,71	0,04	0,96	0,27	0,73	0,13	0,87
	Stayer	0,36	Class 1	1,00	1,00	0,00	1,00	0,00	1,00	0,00	1,00	0,00
			Class 2	0,00	0,00	1,00	0,00	1,00	0,00	1,00	0,00	1,00
I	Mover	0,61	Class 1	0,69	0,92	0,08	0,96	0,04	0,93	0,07	0,87	0,13
			Class 2	0,31	0,18	0,82	0,26	0,74	0,17	0,83	0,16	0,84
	Stayer	0,39	Class 1	1,00	1,00	0,00	1,00	0,00	1,00	0,00	1,00	0,00
			Class 2	0,00	0,00	1,00	0,00	1,00	0,00	1,00	0,00	1,00
EL	Mover	0,76	Class 1	0,47	0,75	0,25	0,78	0,22	0,88	0,12	0,85	0,15
			Class 2	0,53	0,29	0,71	0,12	0,88	0,08	0,92	0,14	0,86
	Stayer	0,24	Class 1	0,38	1,00	0,00	1,00	0,00	1,00	0,00	1,00	0,00
			Class 2	0,62	0,00	1,00	0,00	1,00	0,00	1,00	0,00	1,00
E	Mover	0,93	Class 1	0,49	0,85	0,15	0,97	0,03	0,95	0,05	0,97	0,03
			Class 2	0,51	0,12	0,88	0,00	1,00	0,20	0,80	0,40	0,60
	Stayer	0,07	Class 1	0,02	1,00	0,00	1,00	0,00	1,00	0,00	1,00	0,00
			Class 2	0,98	0,00	1,00	0,00	1,00	0,00	1,00	0,00	1,00
P	Mover	0,90	Class 1	0,62	0,84	0,16	0,94	0,06	0,94	0,06	0,95	0,05
			Class 2	0,38	0,24	0,76	0,12	0,88	0,04	0,96	0,22	0,78
	Stayer	0,10	Class 1	0,00	1,00	0,00	1,00	0,00	1,00	0,00	1,00	0,00
			Class 2	1,00	0,00	1,00	0,00	1,00	0,00	1,00	0,00	1,00
UK	Mover	0,50	Class 1	0,72	0,91	0,09	0,97	0,03	0,98	0,02	0,95	0,05
			Class 2	0,28	0,29	0,71	0,29	0,71	0,23	0,77	0,34	0,66
	Stayer	0,50	Class 1	0,98	1,00	0,00	1,00	0,00	1,00	0,00	1,00	0,00
			Class 2	0,02	0,00	1,00	0,00	1,00	0,00	1,00	0,00	1,00

The response probabilities show that with the subjective deprivation measure, failures to identify a true deprived case and a true non-deprived case are at roughly the same level in four out of ten countries. However, in half of the countries, failure to identify a true deprived case is more common than failure to identify a true non-deprived case. Hence, with the subjective deprivation measure, misclassifying true deprived cases as non-deprived often causes most of the misclassifications. Fewer misclassifications are the type where a true non-deprived case is misclassified as deprived. The largest error in identifying the true deprived can be found in the French and Spanish models, where 40 per cent of the latent (true) deprived are misclassified as non-deprived. Correspondingly, only 3-4 per cent of the true non-deprived cases are misclassified as deprived in these two countries. However, the proportion of the population that is classified as subjectively deprived does not have an association with the level of reliability, though, one might expect that a lower subjective deprivation rate would mean less misclassifications. For example, the subjective deprivation rate is the lowest in the Netherlands, but the model estimates that the subjective measure has an average reliability in the Dutch table.

Since it is difficult to compare (latent) transition probabilities between countries when they are presented separately for the movers and the stayers (whose proportions then vary between countries), we again weight the latent transition probabilities by the π's and this way calculate the overall latent transition rates in the population. In Table 4.4.3 the observed transition rates are once again highlighted and presented below the estimated error corrected transition rates. We can see that in every case the observed transition probability, either inflow or outflow rate, is higher than its latent counterpart. This indicates that measurement error increases observed fluidity, as was expected. The over-estimation seems to be especially high in the transition probabilities from deprived to non-deprived. In other words, much of what appears to be a move out of subjective deprivation is, in fact, error. We could have already concluded this result from the response probability matrixes, which clearly showed that a large part of the true deprived are falsely identified as non-deprived. When comparing the transition probabilities, especially the corrected latent transition probabilities, of the subjective deprivation measure to the transition probabilities of the two objective poverty measures, we cannot help but notice that fluidity seems to be similar with all the three indicators, despite the large differences in marginal distributions. We will return to this in the next chapter.

Finally, the error corrected parameter estimates of the Latent Mover-Stayer model are used to separate the true change and error in the subjective deprivation transition tables. The two top rows of Table 4.4.4 presents the observed proportion of stable cases (OBS) and the observed proportion of change (OBC), which are calculated from the observed frequencies. When comparing the true change (TOC) to the observed change (OBC), we quickly come to the conclusion that measurement error causes the number of mobile cases to be over-estimated in the subjective deprivation transition tables. In other words, the true change is substantially smaller than the observed change in every country. For example, the observed mobility in the Greek and Spanish tables is over 50 per cent of the total sample, but the true change is only 34 per cent in the Greek table and only 24 per cent in the Spanish table. When comparing the true change (TOC) to the observed change (OBC), we can see that mobility in the subjective deprivation transition tables is over-estimated

TABLE 4.4.3: Corrected (latent) and observed transition probabilities for subjective deprivation dynamics

Country	Panel	State at t ↓	t+1=1995 Not Depr	Depr	t+1=1996 Not Depr	Depr	t+1=1997 Not Depr	Depr
DK	Corrected	Not poor	0,97	0,03	0,97	0,03	0,97	0,03
		Poor	0,32	0,68	0,14	0,86	0,25	0,75
	Observed	Not poor	0,95	0,05	0,94	0,06	0,94	0,06
		Poor	0,57	0,43	0,36	0,64	0,49	0,51
NL	Corrected	Not poor	0,98	0,02	0,98	0,02	0,98	0,02
		Poor	0,11	0,89	0,01	0,99	0,09	0,91
	Observed	Not poor	0,94	0,06	0,94	0,06	0,94	0,06
		Poor	0,48	0,52	0,38	0,62	0,46	0,54
B	Corrected	Not poor	0,96	0,04	0,97	0,03	0,96	0,04
		Poor	0,06	0,94	0,29	0,71	0,18	0,82
	Observed	Not poor	0,92	0,08	0,93	0,07	0,93	0,07
		Poor	0,38	0,62	0,47	0,53	0,42	0,58
F	Corrected	Not poor	0,95	0,05	0,97	0,03	0,98	0,02
		Poor	0,12	0,88	0,07	0,93	0,11	0,89
	Observed	Not poor	0,89	0,11	0,89	0,11	0,90	0,10
		Poor	0,48	0,52	0,46	0,54	0,49	0,51
IRL	Corrected	Not poor	0,98	0,02	0,94	0,06	0,98	0,02
		Poor	0,19	0,81	0,02	0,98	0,17	0,83
	Observed	Not poor	0,88	0,12	0,85	0,15	0,88	0,12
		Poor	0,43	0,57	0,32	0,68	0,43	0,57
I	Corrected	Not poor	0,95	0,05	0,98	0,02	0,96	0,04
		Poor	0,11	0,89	0,16	0,84	0,10	0,90
	Observed	Not poor	0,89	0,11	0,90	0,10	0,89	0,11
		Poor	0,41	0,59	0,47	0,53	0,45	0,55
EL	Corrected	Not poor	0,81	0,19	0,83	0,17	0,91	0,09
		Poor	0,22	0,78	0,09	0,91	0,06	0,94
	Observed	Not poor	0,69	0,31	0,70	0,30	0,75	0,25
		Poor	0,29	0,71	0,21	0,79	0,19	0,81
E	Corrected	Not poor	0,86	0,14	0,97	0,03	0,95	0,05
		Poor	0,11	0,89	0,00	1,00	0,19	0,81
	Observed	Not poor	0,76	0,24	0,78	0,22	0,80	0,20
		Poor	0,39	0,61	0,34	0,66	0,43	0,57
P	Corrected	Not poor	0,86	0,14	0,94	0,06	0,94	0,06
		Poor	0,22	0,78	0,11	0,89	0,04	0,96
	Observed	Not poor	0,78	0,22	0,83	0,17	0,82	0,18
		Poor	0,32	0,68	0,28	0,72	0,23	0,77
UK	Corrected	Not poor	0,95	0,05	0,99	0,01	0,99	0,01
		Poor	0,15	0,85	0,14	0,86	0,11	0,89
	Observed	Not poor	0,93	0,07	0,95	0,05	0,95	0,05
		Poor	0,53	0,47	0,55	0,45	0,53	0,47

by 30 to 50 per cent. As a consequence of the over-estimated mobility, stability is under-estimated in the transition tables. This can be seen when comparing the proportions of true stable cases (perfect stability plus TOS) with OBS.

TABLE 4.4.4: Estimated proportions of true stability and change and poverty rate in the subjective deprivation transition tables

	DK	NL	B	F	IRL	I	EL	E	P	UK
OBS	0.77	0.78	0.76	0.67	0.59	0.65	0.49	0.48	0.54	0.78
OBC	0.23	0.22	0.24	0.33	0.41	0.35	0.51	0.52	0.46	0.22
Perf.Stab.	0.54	0.61	0.09	0.21	0.36	0.39	0.24	0.07	0.10	0.50
TOS	0.29	0.29	0.75	0.65	0.44	0.44	0.42	0.69	0.63	0.37
TRS	0.23	0.16	0.64	0.43	0.21	0.25	0.23	0.36	0.41	0.26
error	0.07	0.13	0.11	0.22	0.23	0.20	0.19	0.33	0.22	0.11
TOC	0.17	0.10	0.16	0.14	0.20	0.17	0.34	0.24	0.27	0.13
TRC	0.13	0.05	0.07	0.05	0.10	0.09	0.19	0.08	0.15	0.06
error	0.04	0.05	0.09	0.09	0.10	0.08	0.16	0.16	0.12	0.08
Obs. rate	16,0	13,6	14,0	19,0	32,0	21,7	55,1	36,9	39,8	12,0
Latent rate	14,5	13,6	18,4	26,0	28,9	19,2	55,2	54,7	44,1	14,8

Error seems to operate with a different magnitude in different countries. There seems be an association between the magnitude of error and the level of observed subjective deprivation mobility: countries whit high observed mobility tend to also have higher over-estimation. This association was present also in the financial poverty and housing deprivation transition tables. When error is then removed from the estimates of subjective deprivation mobility, there is less cross-country variation. For example, the Danish table has one of the lowest observed subjective deprivation mobility rates (23 per cent). When purged from error, the Danish table has an average true mobility rate (17 per cent). The opposite is true in the Spanish table, where the observed mobility rate is the highest (52 per cent), and when the over-estimation is corrected, the Spanish table has also an average mobility rate (24 per cent). However, the rank order of countries seems to remain similar.

If error has an effect on the estimates of subjective deprivation dynamics, we can expect that it also has an effect on the cross-sectional rate. We can calculate the latent cross-sectional deprivation rate by multiplying the chain proportion π by the initial proportion δ in the Table 4.4.2 in both chains and then sum the two products. When comparing this error corrected subjective deprivation rate to the observed rate (in 1994) in Table 4.4.4, we can see the error corrected rate gives a somewhat higher estimate for subjective deprivation than the observed rate. Only in Denmark, Ireland and in Italy is the latent subjective deprivation rate lower than the observed rate. In the rest of the countries, the error corrected subjective deprivation rate is somewhat higher than the observed rate. The error corrected rate also shows more cross-country variation than the observed rate. This is perhaps a surprising finding, since the opposite was the case with the two objective measures: the error corrected financial poverty and housing deprivation rates showed less country variation than the corresponding observed rates.

Therefore, it seems that the subjective poverty indicator also gives an affirmative answer to the two research questions that were presented in this chapter: there seems to be more than one transition trajectory in the population and subjective deprivation mobility is over-estimated by 30 to 50 per cent (in the most of the countries), if error is ignored. The population is grouped into three groups that have very different (subjective deprivation) trajectories. The incidences of subjective deprivation are not as equally distributed over the population, as for example, the individualisation thesis seems to suggest. On the other hand, the large proportion of movers in most of the countries supports the individualisation thesis, so again there is mixed evidence for and against the individualisation thesis.

4.5 Conclusions

We were able to model the transition of financial poverty, housing deprivation and subjective deprivation in every country with the same time-heterogeneous (partially) Latent Mover-Stayer model. The model assumes that there are three groups of people in the population and that each group has its own distinctive trajectory: non-mobile cases that never exit poverty (or deprivation), non-mobile cases that never enter poverty (or deprivation) and movers that follow a first-order Markov process. We can conclude that the results of the model fitting support the first research hypothesis: the population seems to be heterogeneous in their relation to the transition of poverty (and deprivation). This means that the risk for poverty (or deprivation) is not equally distributed over the population, instead, parts of the population have higher risk of experiencing poverty spells than others.

The Latent Mover-Stayer model also gives us a means to test the individualisation thesis, although indirectly. We can assume that the smaller the movers' class is, and the bigger the stayers' class is, the more structured poverty is. In other words, the relative size of the movers' class indicates how widely and equally poverty (or deprivation) incidences are distributed in the population. The extreme case would be that there are no movers and the population would be divided into the two groups of stayers: to those always in poverty and to those always out of poverty. Table 4.5 presents the proportion of people always in poverty (or in deprivation), the proportion of people never in poverty and the proportion of movers (calculated from the parameter estimates of the Latent Mover-Stayer model). We can see that usually the majority or at least a half of the population is estimated to be movers. This is the case with all three of the poverty indicators. For example in the three Danish panels, 81 per cent (financial poverty), 97 per cent (deprivation) and 46 per cent (subjective deprivation) of the population is estimated to be movers. It seems to be usual that the majority of population live under the risk of poverty, although the risk is often rather small. This observation is congruent with some aspects of the individualisation thesis, namely that poverty also reaches the middle classes in the contemporary welfare state. On the other hand, we can see that the other half of the population are stayers. For example, in the Netherlands and Italy around a half of the population is expected never to experience poverty or deprivation. Even in Denmark, where the majority is estimated to be movers with the two objective measures, the subjective measure indicates that 51 per cent never experience subjective deprivation. Also in many countries the proportion of people living under constant poverty is substantial (like in Greece, Spain and Portugal). These examples would suggest that poverty is (still) very much a structural phenomenon. So the answer to the question is poverty 'democratic' and 'transitory' in the contemporary post-industrialised society depends on what aspects of poverty mobility we focus on: the proportion of movers or the proportion of (non-poor) stayers. But a severe interpretation of the individualisation thesis does not receive support from our empirical results.

The common longitudinal structure that poverty and deprivation seem to have across countries indicates that the same macro-structural factors shape the longitudinal structure of social disadvantages. We can assume that the structure of disadvantages arises from the different positions in the production labour (see chapter 1.2.2.), in a similar way as the structure of social stratification does.

TABLE 4.5: Proportions of movers and stayers in population

	DK	NL	B	F	IRL	I	EL	E	P	UK
Financial										
Movers	80.5	83.1	41.3	36.9	66.7	52.3	55.6	40.7	76.1	50.7
Stayers in										
poverty	1.1	2.5	0.0	5.1	3.6	2.6	2.3	2.8	8.2	3.3
non-poverty	18.4	14.5	58.8	58.0	29.8	45.1	42.1	56.5	15.8	46.0
Deprivation										
Movers	97.0	40.7	34.4	94.1	54.7	43.7	79.5	50.2	76.4	52.3
Stayers in										
deprivation	0.4	0.0	1.9	1.8	0.0	0.9	0.3	0.0	5.9	0.9
non-depriv.	2.6	59.3	63.7	4.1	45.3	55.4	20.2	49.8	17.7	46.8
Subjective										
Movers	46.3	39.2	91.5	79.8	64.0	61.1	76.0	92.6	89.6	49.9
Stayers in										
deprivation	2.8	1.3	3.0	2.1	0.0	0.0	14.9	7.3	10.4	0.9
non-depriv.	50.9	59.6	5.6	18.2	36.0	38.9	9.1	0.1	0.0	49.1

Naturally, the structure of poverty and deprivation is shaped by institutional arrangements of the welfare state and family. However, what is interesting is that the structure of disadvantages is the same across the countries that have different welfare state arrangements. We will return to this in the final conclusion chapter.

The second research question that is addressed in this chapter is whether poverty dynamics are over-estimated, if random error is ignored. The parameter estimates of the Latent Mover-Stayer model were utilised to separate true change and error. In the measurement sub-model of the Latent Mover-Stayer model we made the assumption that errors are independent over waves, which is not necessarily a valid assumption. However, we cannot test this assumption with the data we have (see Breen & Moisio 2004). The measurement error is mainly associated with the failure to accurately identify the poor, the non-poor are identified with much less error. These failures – where a true poor case is misclassified as non-poor – means that much of what appears to be exits from poverty (or deprivation) in the panel is actually error. Error-corrected parameter estimates indicated that mobility in poverty (and deprivation) panels is over-estimated in most of the cases by 25 to 50 per cent if the random error is ignored. Error corrected estimates also show that not only does correcting for measurement error influence conclusions we might draw regarding any single country but also, because these errors operate with differential effect in the various countries, they also lead us to different conclusions about country comparisons. Therefore, we have seen that once error is corrected, the ordering of countries in terms of the size of their flow into and out of poverty can change. This change was particularly striking among some Southern-European countries, whose relative position on the ranking of poverty (and deprivation) mobility dropped often from the top to the bottom when error was corrected.

It seems that Duncan's (1997) concern about the possibility of measurement error in longitudinal poverty studies and the consequent risk of over-estimating poverty mobility is everything but irrelevant. Analyses in this chapter showed that in some cases over half of the observed mobility is just random error, noise. The danger of over-estimating poverty mobility needs to be taken more seriously now especially because longitudinal poverty measures are gaining more visibility in the EU policymaking. Eurostat's decision to incorporate a longitudinal poverty measure into the structural indicators is one example of the growing influence of longitudinal poverty measures in policymaking (see Eurostat 2003). It has been accepted that analysing poverty as a longitudinal phenomenon is essential both to our understanding of it and to the development of social policy. Now we should also accept that longitudinal measurement requires error correction, since random error has a different effect in longitudinal poverty measurement than in cross-sectional. In other words, the expected and true values of a cross-sectional estimate are equal, but this is not the case with estimates describing transitions and dynamics in the panel data. In panel data, if random error is not incorporated into the measurement model, all misclassifications are read as mobility and the estimates of dynamics are thus over-stated.

We have seen that the transition probabilities in the financial poverty, deprivation and subjective deprivation transition tables are similar, especially when the effect of random error is removed. In the next chapter we will test if the pattern of fluidity is common in the transition tables of direct, indirect and subjective indicators.

5 Comparing poverty dynamics across indicators

5.1 Introduction

The log-linear modelling in chapter four showed how the population can be divided into three groups each with very different poverty (or deprivation) mobility trajectories. The associations in the financial poverty, housing deprivation and subjective deprivation transition tables were crystallised into a classical Mover-Stayer model that allows error in the measurement. We also discovered that the observed poverty transition probabilities were surprisingly similar between the three indicators that have very different marginal distributions. The error corrected (true) transition probabilities show even more similarity across the three indicators than the observed probabilities. The obvious continuation from here is to test whether the transition probabilities that describe the pattern of fluidity are common in the transition tables of financial poverty, housing deprivation and subjective deprivation.

In this fifth chapter we test the third research hypothesis that states that different poverty classifications have common dynamics. This hypothesis is derived from David Gordon's (2002, 15) thesis that direct and indirect poverty indicators measure the same dynamic process of poverty, but in its different phases. The empirical method to test the possible commonality of poverty and deprivation dynamics is to combine the three transition tables into a layered table and fit a model assuming a common pattern of transition probabilities in the layer. Each transition table ABCD is now treated as a category of a new variable M that has three categories (or layers): financial poverty transition, housing deprivation transition and subjective deprivation transition.

In the next section the Common Fluidity model and the Latent Common Fluidity model are presented and then tested with the layered MABCD tables to find out if the pattern of fluidity is common to all three poverty indicators. In the third section we study more closely the transition probabilities by comparing the latent and observed inflow (into poverty) and outflow (out of poverty) probabilities between the three classifications. The fourth section summarises the empirical findings made in the chapter.

5.2 Common pattern of fluidity between indicators

When testing the hypothesis that the pattern of fluidity is common across the three transition tables, we use a method that is widely used in studies of social mobility (e.g. Erikson & Goldthorpe 1992). We treat our three transition tables as if they were mobility tables from different countries and construct a layered table from them by creating a new variable M, which indicates the layers. The value I (labelled I) in the new variable M indicates the financial poverty transition table, the value II (labelled D) indicates the housing deprivation transition table and the value III (labelled S) indicates the subjective deprivation transition table. The variable M is then treated like any other categorical variable in the log-linear models. If we continue to label the repeated classifications in 1994, 1995, 1996 and 1997 as A, B, C and D, we can present the layered transition table as MABCD.

We can test the assumption that the fluidity in the three transition tables ABCD is common with a model that assumes a common pattern of transition probabilities in the layers of M. The model would be equivalent to the Constant Social Fluidity model that is often used in social mobility studies to compare the transition probabilities between the social origin and destination at different times (Erikson & Goldthorpe 1992). Here we use the Common Fluidity (CF) model to test the hypothesis that the pattern of fluidity, i.e. the transition probabilities, is common in the poverty and deprivation transition tables. The Common Fluidity model assumes that A, B, C and D can have different marginal distributions in the classes of M, but all the associations between A, B, C and D are constant across the classes of M. (See Appendix A.)

However, a weakness of the CF model is that it does not assume, to be precise, that the fluidity is common in the layers of M: the CF model assumes that the *sum* of fluidity and error is common in the layers of M. We can eradicate this weakness by incorporating error into the CF model. The Latent Common Fluidity model (LCF) has the measurement component that relates each observed measure A, B, C and D to the structural component of the model with a probabilistic relationship, allowing a separate error for each manifest variable. The structural component of the LCF model is the exact copy of the CF model, although the associations in the {ABCD} table are now assumed to be mediated trough the latent structure {VWXY} (see Appendix A). So the Latent Common Fluidity model assumes common fluidity between A, B, C and D in the categories of M, as in the CF model, but the LCM model relates A, B, C and D to the latent structure that represent the common fluidity with probabilistic relationships allowing for error in their measurement.

Table 5.1 presents model fit diagnostics for the Common Fluidity and the likelihood ratios for each M layer separately. The CF model has 22 degrees of freedom and the misclassifications (Δ) vary from the Netherlands's 1.3 per cent to

TABLE 5.1 Common Fluidity and Latent Common Fluidity models and their Likelihood ratios for each transition tables separately

		CF		Sub-tables of M		
	df	G2	Delta	G2 in I	G2 in D	G2 in S
DK	22	271.0	2.4	45.0	96.1	129.9
NL	22	134.0	1.3	48.5	57.1	28.4
B	22	326.1	2.9	104.4	95.4	126.3
F	22	916.8	4.7	513.4	95.2	308.2
IRL	22	566.4	4.0	175.3	211.0	180.2
I	22	381.8	2.9	70.3	118.0	193.5
EL	22	671.1	4.7	339.5	77.0	254.6
E	22	914.6	4.4	210.7	348.5	355.4
P	22	976.0	5.7	387.5	139.3	449.2
UK	22	190.3	2.1	72.6	42.2	75.4

		LCF		Sub-tables of M		
	df	G2	Delta	G2 in I	G2 in D	G2 in S
DK	16	228.8	2.2	49.6	93.6	85.5
NL	16	114.3	1.1	31.4	58.0	24.9
B	16	261.2	2.4	63.0	75.6	122.6
F	16	171.3	1.4	28.2	93.2	49.9
IRL	16	364.8	2.4	142.2	130.5	92.1
I	16	107.5	1.0	26.8	37.9	42.8
EL	16	272.6	2.4	112.4	49.5	110.7
E	16	377.3	2.2	131.1	70.6	175.5
P	16	488.1	3.2	201.5	80.6	206.0
UK	16	90.9	1.3	20.6	33.2	37.1

Portugal's 5.7 per cent. The average misclassification among the ten countries is around four per cent. So it seems that the CF model does not have a particularly good fit. If we study the likelihood-ratios (G^2) separately in each transition table we can evaluate where the mismatch between the observed and estimated model occurs. A separate likelihood-ratio estimate for each M layer is calculated from the fitted values of the CF models and the Ns are standardised, since the transition tables contain a somewhat different number of cases due to missing cases (Erikson & Goldthorpe 1992, 116). By breaking down the likelihood ratio like this we can study whether one of the layer(s), i.e. transition table(s), causes more mismatches between the estimated and observed frequencies than the others. For example, in Portugal the LC model has a clearly poorer fit in the subjective deprivation transition table than in the financial poverty or the housing deprivation transition tables: 46

per cent of the overall likelihood ratio is produced in the subjective deprivation layer (449.2/976.0). But in the rest of the countries we cannot really point to a transition table that would be the 'weakest' i.e. causing more mismatch than the other two tables.

We might expect that one reason for the poor fit of the Common Fluidity model is that it does not allow for error in the model. When observing the fit of the model diagnostics for the Latent Common Fluidity model in Table 5.1, it seems that this expectation is correct: the Latent Common Fluidity model has a better fit than the Common Fluidity model in every country, indicating that the true fluidity shows less variation than the observed fluidity between the three transition tables. The LCF model has 16 degrees of freedom, as including four stationary 2*2 reliability matrixes into the model takes six degrees of freedom. But the LCF model decreases the likelihood ratio value by 15 to 81 per cent when compared to the CF model. In some countries, taking error into account increases the model fitness dramatically. For example, in the French table the misclassification is 1.4 per cent of all cases with a G^2 value of 171.3. Hence, the decrease in the Δ value is over 70 per cent compared to the CF model (4.7 to 1.4 per cent). The best fit can be found in the Italian table where the LCF model misclassifies only 1.0 per cent of the cases with a G^2 value of 107.5. The LCF model has a good fit in many other countries too. For example, in the Dutch, the French and the UK tables, the LCF model misclassifies less than one and a half per cent of all cases.

When comparing the likelihood ratios in each transition table separately under the LCF model, we can notice that none of the transition tables clearly stand out as a 'deviant' from others: not even in countries where the LCF model fits less well. However, in some countries, even a half of the total G^2 value is produced in one transition table. For example, in the French table, 54.4 per cent of the total G^2 value is produced in the housing deprivation layer. However, when observing all ten countries, we can see that none of the layers are systematically producing more mismatches than the others between the LCF model and the observed data.

The hypothesis that the direct, indirect and subjective poverty indicators have a common pattern of fluidity does get prudent support, at least in the four countries mentioned (Italy, Denmark, France and the UK). The reason why the Latent Common Fluidity model does not have a particular good fit in some countries, e.g. in the Portuguese table, cannot be seen as a fault of any particular indicator. In other words, each country seems to have some unique differences between the transition probabilities of financial poverty, housing deprivation and subjective deprivation: in some countries it is the fluidity in the deprivation table that seems to differ from the fluidity in the financial and subjective deprivation tables, in other countries it is the fluidity in income or subjective deprivation table that is different. However, it has to be noted that the variation in the error-corrected transition probabilities between the three transition tables is strikingly small in every country. We will now study more closely the pattern of fluidity in the three transition tables by looking to the observed and error-corrected transition probabilities that describe the inflows to and outflows from poverty (and deprivation).

5.3 Error corrected absolute and relative mobility rates

The better the fit that the Latent Common Fluidity model has with the data compared to the Common Fluidity model indicates that the error-corrected transition probabilities show less variation between the transition tables of indirect, direct and subjective measures than the observed transition probabilities. However, the overall model fitting is a rather rough method for comparing the patterns of fluidity. Often mobility in a transition table is analytically broken down into absolute and relative mobility that can be seen as two aspects of the same phenomenon – mobility. Absolute mobility refers to the absolute number (or proportion) of cases that have moved, in other words, changed their status in the panel. Relative mobility, usually called *fluidity*, refers to the transition probabilities that a case may change its status between the measurement point t and $t+n$. We follow this analytical breaking down of mobility and study absolute mobility and fluidity separately.

Figure 5.1 presents the observed absolute mobility rate (light grey bar) and the error corrected absolute mobility rate (dark grey bar) of financial poverty, housing deprivation and subjective deprivation in each country. These absolute mobility rates are the same as presented in the tables 4.2.4, 4.3.4 and 4.4.4. The absolute mobility rates are only presented visually to make comparisons more easily. With every indicator, the observed absolute mobility is over-stated as was reported in chapter four. However, the over-estimation seems to be a different size with every indicator. Absolute mobility in the subjective deprivation transition tables seems to be over-estimated more than in the transition tables of objective poverty measures. Especially in the Southern-European countries and in Ireland, observed absolute mobility in the subjective deprivation table contains a larger error than observed mobility in the financial poverty or deprivation table. However, the error corrected absolute mobility rate shows much less variation between the three transition tables. A suggestion of this was received in the previous section where the Latent Common fluidity model showed a much better fit to the data than the Common Fluidity model. Also, the rank order between indicators changes when error is removed from the absolute mobility rates. The subjective deprivation transition table has the highest mobility rates in every country (except in the UK), but when error is removed, subjective deprivation has the highest mobility rates only in the four Southern-European countries. In the rest of the countries the highest true mobility rate can be found either in the financial poverty or deprivation table.

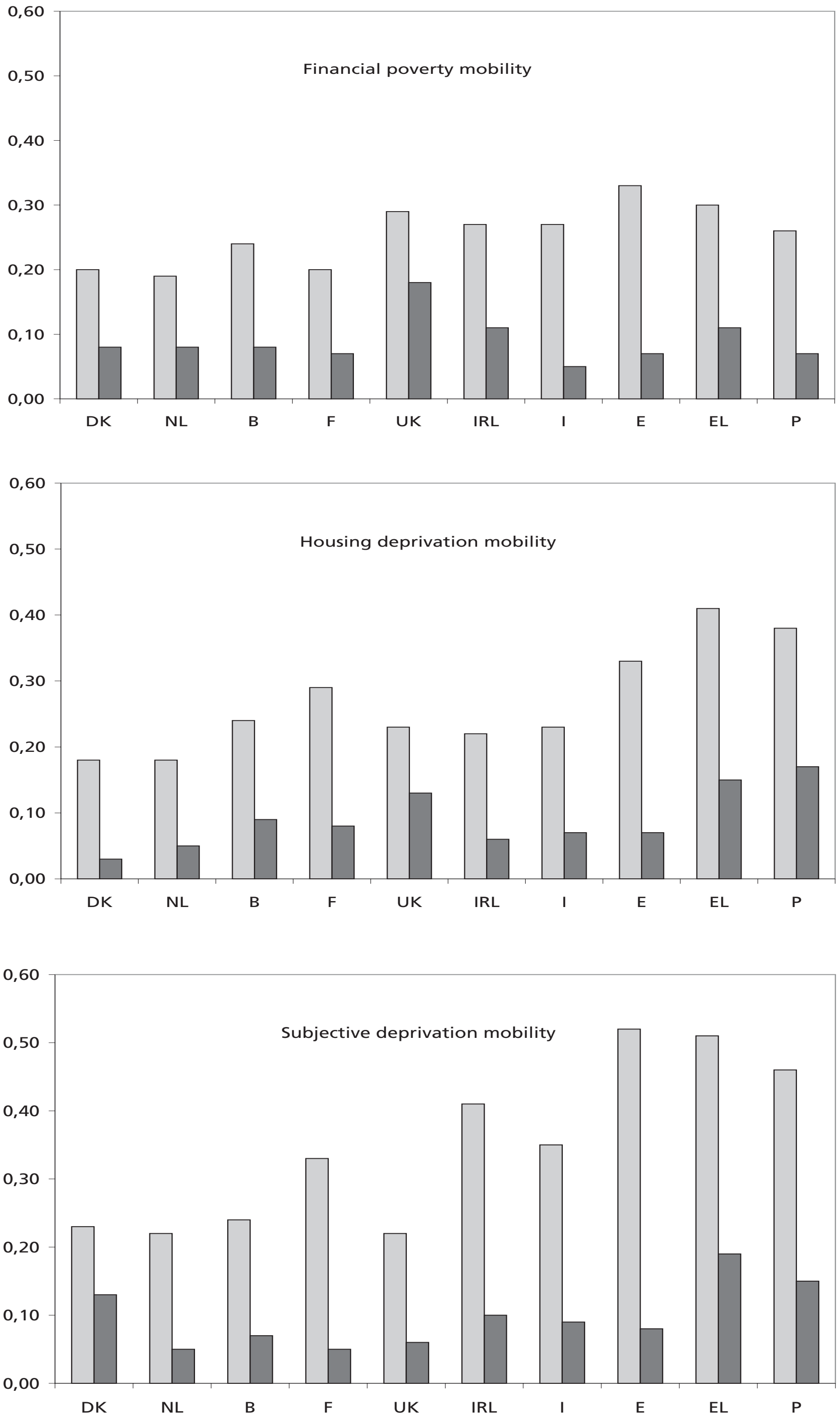

FIGURE 5.1 Observed (left bar) and true (right bar) absolute mobility rates in financial poverty, housing deprivation and subjective deprivation transition tables

Absolute mobility indicates the proportion between those who have changed their status compared to those who have not. Fluidity indicates the likelihood(s) that a case changes its status in the panel. Figures 5.2 and 5.3 present the true and observed fluidity as inflow rates into poverty (or deprivation) and outflow rates out of poverty (or deprivation). The error corrected inflow and outflow rates are calculated from the parameter estimates of the Latent Mover-Stayer model and the observed rates are calculated from the observed frequencies (see tables 4.2.3, 4.3.4 and 4.4.3).[21] The observed inflow and outflow rates are indicated with a light grey bar, the error corrected rates with a dark grey bar. The first thing that can be noticed when looking at Figure 5.2 is that the error corrected inflow rate is slightly lower than the observed inflow rate in every country and with every indicator. This means that error causes the observed inflow rate to somewhat over-estimate the average risk to fall into poverty (or deprivation). We can see also that the error corrected inflow rates of the three indicators are close to one another in countries where the LCF model has a good fit. For example, the true inflows of financial poverty, deprivation and subjective deprivation are the same level in the Netherlands, in France, in Italy and the UK. On the contrary, in countries where the LCF model indicates that the pattern of fluidity is not common between indicators, the true inflow rates of the three indicators are also different, as in Greece and in Portugal. However, the over-estimation in the observed inflow rate seems to be quite similar, usually around 50 to 100 per cent, except with the inflows of deprivation and subjective deprivation in the Southern-European countries (Italy being the exception) that have a much higher over-estimation. The main finding is the same as with the absolute mobility rate: the error-corrected inflow rate shows much less variation between the financial poverty, housing deprivation and subjective deprivation tables than the observed inflow rate.

Figure 5.3 presents the observed and error corrected outflow rates. As we expected, the observed outflow rates are over-estimated in every transition table. For example in Denmark, the observed outflow out of financial poverty is .50, but the true probability of exiting financial poverty is only .12. When comparing Figure 5.2 and 5.3, it seems that the observed outflow is over-estimated even more than the inflow. This finding is congruent with the conclusion we draw from the response probability (reliability) matrixes in chapter four: a large part of the observed transitions out of poverty and deprivation is in fact measurement error. We can also notice that the variation of the true outflow rate between the three indicators is smaller than the variation in the observed outflow rate, an observation that again is congruent with the previous results.

[21] We cannot use the parameter estimates of the Latent Common Fluidity model to estimate the error corrected (two-way) inflow and outflow rates because the model assumes all possible two-way, three-way and four-way associations to be in the model. Since the Latent Mover-Stayer model is time-heterogeneous, which makes visualisation of transition probabilities difficult, the inflow and outflow rates in figures 5.1 and 5.2 are simple averages of the three latent transition probabilities.

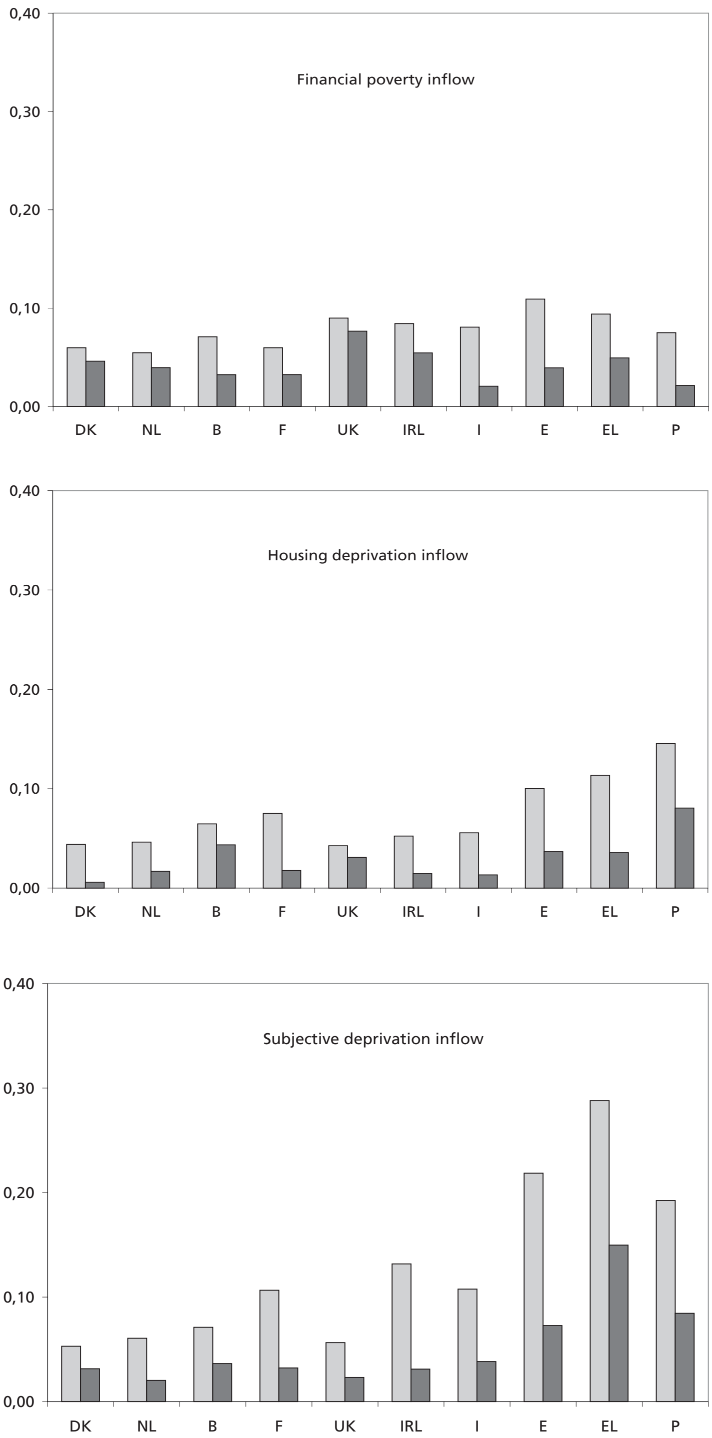

FIGURE 5.2 Observed (light/left bar) and true (dark/right bar) inflow rates in financial poverty, housing deprivation and subjective deprivation transition tables

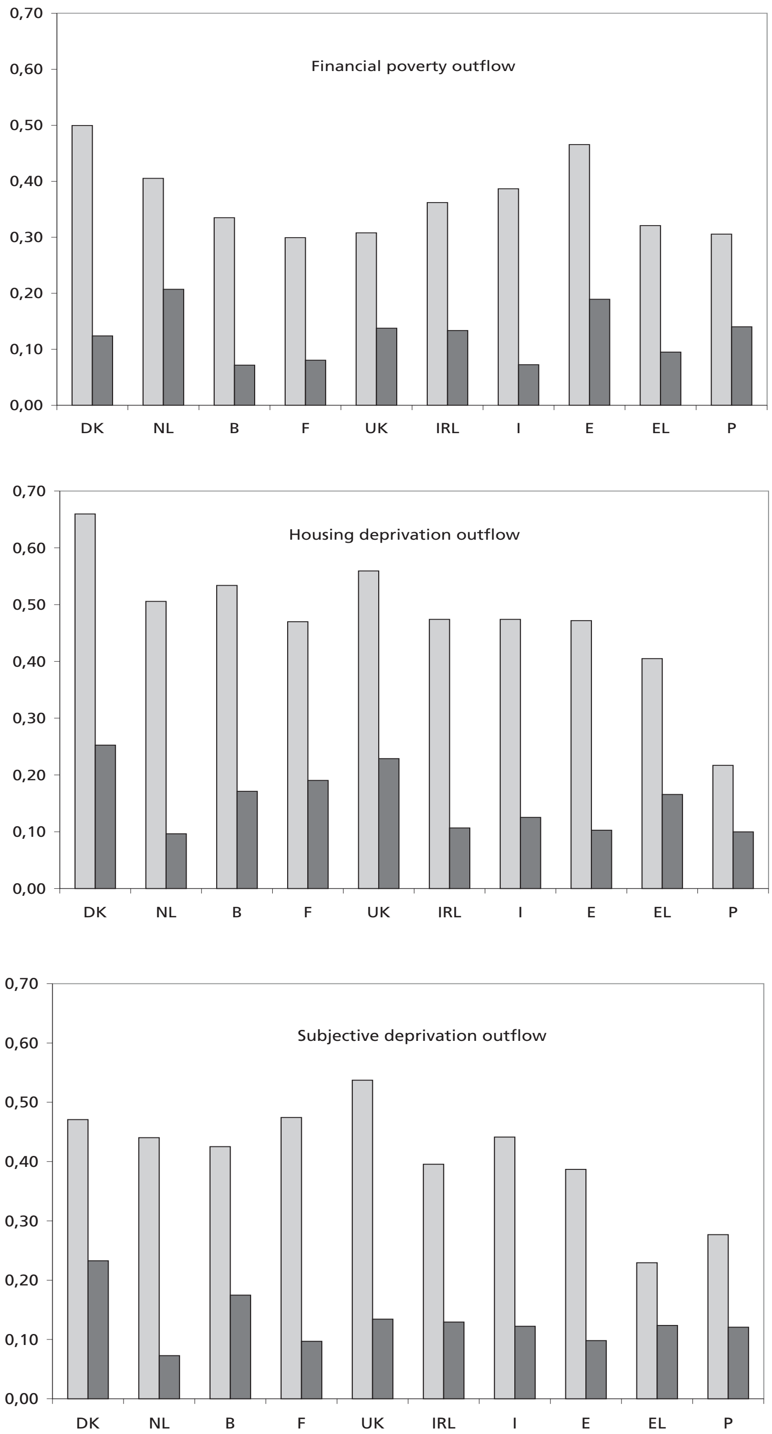

FIGURE 5.3 Observed (light/left bar) and true (dark/right bar) outflow rates in financial poverty, housing deprivation and subjective deprivation transition tables

5.4 Conclusions

The answer to the third research hypothesis, i.e. that direct, indirect and subjective poverty indicators have the common structure of dynamics, is a cautious yes. There seems to be, if not a common, then at least a very similar pattern of fluidity in the transition tables of financial poverty, housing deprivation and subjective deprivation. However, there are differences in the observed absolute mobility rate as well as in the transition probabilities, but a large part of this variation is due to measurement error. The first suggestion of this came when the Latent Common Fluidity (LCF) model was discovered to have a much better fit to the data than the Common Fluidity model. The Latent Common Fluidity model is a measurement model, where the structural part of the model assumes the common pattern of fluidity in the transition tables of financial poverty, deprivation and subjective deprivation. The measurement part of the model assumes that each manifest indicator relates to this structural component imperfectly, allowing each manifest measurement to have a separate error. We also studied the likelihood ratios under the LCF model separately in each layer and could not find any evidence that one of the indicators would have a deviant pattern of fluidity compared to the other two indicators.

The mobility in the three transition tables was then compared in a more detailed way by studying the observed and latent estimates of absolute mobility and fluidity. It seems that not only the absolute mobility is over-estimated if random error is ignored, but also poverty and deprivation fluidity is over-estimated if error is not corrected. The observed outflow rate especially vastly over-states the true outflow, while the gap between the observed inflow and the error corrected inflow is not that large. The high over-estimation at the observed outflow rate indicates that much of what appears to be an exit from poverty (or deprivation) is in fact error. The error corrected estimates for absolute mobility and fluidity also show much less variation between the transition tables of financial poverty, housing deprivation and subjective deprivation, as we may have expected on the basis of the Latent Common Fluidity model. This is especially the case when the higher than average over-estimation of absolute mobility and inflows in the subjective deprivation transition table is corrected; then the true absolute mobility and fluidity rates show clear affinity across the three transition tables. What is also noticeable is that the dynamics of financial poverty, deprivation and subjective deprivation showed no signs of any constant rank order in the ten countries, either before or after correcting error. In other words, in some countries subjective deprivation showed the highest mobility rates, but in other countries financial poverty or deprivation had the highest mobility rates.

So, despite the fact that indirect, direct and subjective poverty indicators are giving very different cross-sectional poverty rates, their patterns of fluidity seem to have a high degree of similarities. Additionally, much of the variation both in observed absolute mobility as well as poverty fluidity rates is caused by measurement error - the error corrected absolute mobility and fluidity show much less variation between the three indicators. Correcting error gives lower absolute mobility, inflow and outflow rates, but the 'rank order' between the financial poverty, housing deprivation and subjective deprivation measures does not usually change. In other words, an indicator that has a higher observed mobility rate, tends to also have a higher true mobility rate. But this relationship does not seem to apply when we compare the true and observed mobility estimates across countries. We have discovered that the rank order of the countries according their absolute mobility rate can change dramatically when the error is removed. For example, Italy has one of the highest observed absolute poverty and deprivation mobility rates, but one of the lowest true absolute mobility rates. We will now turn to country comparisons in the next and final empirical chapter.

6 Comparing poverty dynamics across countries

6.1 Introduction

One advantage of using a comparative research setting is that differences and similarities in attributes between groups and cases can often tell us something about the attribute itself. For example, there are different types of welfare states throughout the EU countries. Comparative welfare research has pointed out that the present-day welfare states in the European Union can be grouped into three or four regimes and similarities inside a regime can be explained by a certain socio-historical development (Esping-Andersen 1990). Countries that have a similar type of welfare state seem to also have a similar history of industrial relationships and political party coalitions, for example. Without a comparative approach, the socio-historical underpinning that explains the differences between contemporary welfare states would have been difficult to discover. When observing poverty mobility in a single country, it is also difficult to interpret whether the observed mobility is high or its pattern unique unless we have something with which we can compare the estimates of mobility. Comparisons between countries enable us to evaluate whether the pattern or level of poverty mobility is unique or common between countries and in this way comparisons also give a base for an explanation of poverty mobility.

In this final empirical chapter, we test the last remaining research hypothesis, namely that the pattern of poverty (and deprivation) fluidity is common across countries. One alternative to there being a common poverty fluidity pattern would be that there is no regularity between the countries. There may be some kinds of 'poverty fluidity regimes' that assign countries into groups by poverty fluidity patterns. Some previous empirical research findings support the common fluidity hypothesis. On the other hand, some welfare state theories support the idea of fluidity regimes. We can expect that there is some regularity in the pattern of fluidity between countries, either commonality or regimes. The Common Fluidity and Latent Common Fluidity models are now fitted to three layered transition tables, where the layers now represent countries and the model fit is studied separately in each layer. The model fitting is made in section two, where the common poverty fluidity -hypothesis is tested formally. In section three, we try to explain how poverty (and deprivation) fluidity can show a high affinity between countries, while there are large differences in the national poverty rate. The fourth section summarises the empirical findings.

6.2 Common pattern of fluidity between countries

If we continue to use the same variable labels A, B, C and D for the repeated classifications in 1994, 1995, 1996 and 1997, we can present the transition tables as ABCD. The ABCD transition tables of financial poverty, deprivation and subjective deprivation were combined into a single layered frequency table in the previous chapter and these layered transition tables were studied separately in each country. Now the ABCD transition tables of financial poverty are combined across countries into one layered table and the same thing is done to the ABCD tables of housing deprivation and subjective deprivation. A new categorical variable T is created that has ten categories, each category representing a country layer, and the three layered tables can be presented as TABCD. We can now test if the poverty (and deprivation) fluidity is common across countries by testing if the pattern of fluidity is common in the categories of T.

We use the same Common Fluidity (CF) and Latent Common Fluidity (LCF) models that were used in chapter five (see Appendix A) to test the affinity between countries in observed and true relative mobility. The Common Fluidity model assumes again that A, B, C and D can have different marginal distributions in the classes of T, but all the transition probabilities between A, B, C and D are constant across the classes of T, i.e. the fluidity pattern is constant across the countries. The CF and LCF models differ from each other only in that the latter allows for error in the model by relating the manifest measurements A, B, C and D to the latent structure (which represents the common fluidity in this case) in probabilistic ways. Table 6.1 presents the model fit diagnostics for the CF and the LCF models that are fitted to the three TABCD tables, and the likelihood ratios are presented separately for each country. The Common Fluidity model has 99 degrees of freedom and the poorest fit can be found with the layered subjective deprivation transition tables: the G^2 has value of 2681.1 and the misclassification is 4.6 per cent. Hence, the pattern of fluidity in the layered subjective deprivation transition table shows more country variation than is observed in the financial poverty or deprivation transition tables. The pattern of fluidity in the layered financial poverty and housing deprivation transition tables seems to be similar between countries: in the layered financial poverty transition table the Common Fluidity model misclassifies 3.7 per cent of the cases with the G^2 value of 2008.2, in the layered housing deprivation table it is 3.5 per cent with the G^2 value of 2011.1.

When studying the likelihood ratios under the Common Fluidity model separately for each country, one country stands out in every layered transition table: Spain. The Spanish sub-table alone produces 45.8 per cent of the likelihood ratio value in the layered financial poverty transition table, 24.6 per cent in the housing deprivation table and 35.7 per cent in the subjective deprivation table.[22]

[22] Since the national samples in the ECHP are different in their sizes we have standardised the Ns by weighting G^2 by the sample size. Otherwise countries with large samples would 'weigh' more in the comparison (see Erikson & Goldthorpe 1992, 116).

TABLE 6.1 Likelihood ratios for each country table separately under the Common Fluidity and Latent Common Fluidity Model

		Income		Deprivation		Subjective	
Model	df	G2	Delta	G2	Delta	G2	Delta
CF	99	2008,2	3,7	2011,1	3,5	2681,1	4,6
LCF	79	1122,2	2,3	1263,2	2,2	1275,0	2,7
Weighted percentage of the total G2 values produced							
		CF	LCF	CF	LCF	CF	LCF
	DK	1,6	3,2	3,7	5,0	3,4	2,1
	NL	3,6	3,2	3,3	3,7	10,1	4,2
	B	3,6	5,4	7,7	8,5	4,9	3,7
	F	15,1	6,1	12,7	17,9	2,6	2,8
	IRL	5,4	8,7	7,8	9,0	3,7	9,1
	I	6,9	8,1	6,4	5,3	5,9	10,1
	EL	3,6	5,6	13,7	8,6	16,2	16,8
	E	45,8	37,3	24,6	22,3	35,7	28,4
	P	9,1	11,0	18,1	17,5	13,7	20,6
	UK	5,3	11,5	2,0	2,3	3,5	2,2
		100	100	100	100	100	100

The pattern of observed financial poverty fluidity is different in Spain because Spain has a higher observed inflow and outflow rate (see Figures 5.2 and 5.3) as well as higher observed absolute mobility rate (see Figure 5.1) compared to other countries. In the transition tables of housing deprivation and subjective deprivation, the observed outflow or inflow rates are not very different in the Spanish sub-table from what can be seen in the other countries. Also the observed absolute deprivation or subjective deprivation mobility rates are not higher in Spain when compared to the other countries. In the TABCD tables of housing and subjective deprivation, the reason for the poor fit of the model in the Spanish sub-table is that the observed inflow and outflow rates seem to more time-heterogeneous in the Spanish sub-table than in the other sub-tables (see Tables 4.3.3 and 4.4.3). The Common Fluidity model is time-heterogeneous, allowing even the four-way association in the ABCD sub-table, but the model assumes that the transitions are time-heterogeneous in the same way for each country.

We have learnt that error not only causes the absolute mobility and fluidity to be over-estimated in transition tables, but that error can increase the variance of absolute and fluidity rates between countries (and indicators). This is because error seems to operate on a different level in different countries. One possible source of mismatch between the Common Fluidity model and the data is that the Common Fluidity model is a structural model that allows for no error in the measurement. The Latent Common Fluidity (LCF) model tests the hypothesis that the true pattern of fluidity is common between countries by allowing each country and each repeated poverty and deprivation classification to have its own separate error. This means that the different level of error between countries (and between A, B, C and D) is no longer read as variation. The LCF model has 79 degrees of freedom and the model again has a better fit to the transition tables of objective indicators than to the transition table of subjective deprivation, as was the case with the Common Fluidity model. So it seems that true fluidity, not only observed, shows the largest country variation in the layered subjective deprivation transition table. The Latent Common Fluidity model misclassifies 2.7 per cent of all cases with the G^2 value of 1275.0 in the TABCD table of subjective deprivation. When comparing the likelihood ratio and the misclassification produced by the LCF model to the likelihood ratio and misclassification produced by the CF model, we can see that incorporating error into the model decreases the G^2 value by 52.4 per cent (with the loss of 20 degrees of freedom) and the misclassification drops by 41.5 per cent. Therefore, it is obvious that the Latent Common Fluidity model has much better fit than the Common Fluidity model in the TABCD table of subjective deprivation. However, the fit of the LCF model is not perfect, as the model still misclassifies 2.7 per cent of all cases.

In the TABCD tables of financial poverty and housing deprivation, the Latent Common Fluidity model also has a much better fit than the Common Fluidity model. In the TABCD table of financial poverty, the LCF model has the likelihood ratio value of 1122.2 and the misclassification of 2.3 per cent of the all cases: the decrease in the G^2 value is 45 per cent (with the loss of 20 degrees of freedom again) and the decrease in the Δ value is 38 per cent when compared with the Common Fluidity model. In the TABCD table of housing deprivation, the Latent Common Fluidity model has the G^2 value of 1263.2 with 2.2 per cent of the cases misclassified: the decrease in both the likelihood ratio and in the misclassification is 37 per cent compared to the Common Fluidity model. So the pattern of true (or error corrected) fluidity seems to be much more similar between countries than the pattern of observed fluidity. The explanation for this is that the over-estimation of (absolute as well as relative) mobility is not common across countries. In some countries, for example in Spain, observed absolute mobility is high, but a large part of this mobility is error, so the true mobility is not higher in Spain than in other countries. On the contrary, the true absolute mobility is lower in Spain than in the most of countries. Also the observed inflow and outflow rates of subjective deprivation are over-estimated to a larger degree in Southern-European countries. However, once error is removed from the estimates of subjective deprivation fluidity, Southern-European countries also show a high affinity with the rest of the countries.

We can study the source of mismatch between the data and the Latent Common Fluidity model more closely by calculating the misclassifications separately for each country-layer, as was done in chapter five. When observing the standardised likelihood-ratio values in Table 6.1, we can see that Spain stands out again. The Spanish sub-table, or the layer of T, in the TABCD table of financial poverty is responsible for 37.3 per cent of the overall likelihood ratio value, calculated as the proportion of the (adjusted) G^2 value in the Spanish sub-table from the overall G^2 value. The proportion of the likelihood ratio produced by the Spanish layer is lower in the TABCD table of housing deprivation and subjective deprivation. In the layered housing deprivation table, the Spanish sub-table is responsible for 22.3 per cent of the overall likelihood ratio value, in the layered subjective deprivation table it is 28.4 per cent. The probable explanation for why the pattern of true financial poverty fluidity seems to be different in Spain is the high time-heterogeneity in the true outflow rates. This can be seen in the error corrected transition probabilities in Table 4.2.3. The outflow rate in the Spanish financial poverty table is .34 between the first and second measurement point (A and B), .04 between the second and third measurement points (B and C) and .18 between the third and fourth measurement points (C and D). Hence, the latent outflow rate varies enormously across time in the Spanish table, while in the other countries, the latent outflow rates are relatively time-homogeneous. The extremely high variation in the transition probabilities may also be a sign of some considerable errors of nonobservation in the Spanish panel data.

When the estimates of the true and observed change were compared in chapter four, we came to the conclusion that absolute mobility is over-estimated by 25 to 50 per cent and that there is less country variation in the level of absolute mobility after random error is removed (Tables 4.2.4, 4.3.4 and 4.4.4). The Latent Common Fluidity model and the error corrected inflow and outflow rates indicate that we can draw a similar conclusion about fluidity. The error corrected transition probabilities indicate a lower level of fluidity and less cross-country variation in the pattern of fluidity than what would be interpreted from the observed estimates. If we look again figures 5.1, 5.2 and 5.3, but this time comparing countries, we can see that the error corrected inflow rate is always lower than its observed counterpart in every country. It further seems that the error-corrected inflow rate shows less country variation than the observed rate. However, the higher country variation in the observed inflow rate seems to be caused mainly by the Southern-European countries (and to some degree Ireland and France), where the over-estimation of inflows are relatively higher than in the rest of the countries. This means that the observed inflow rate is higher in the Southern-European countries, though the true inflow rate is at the same level as in the other countries. When removing error from the absolute mobility rate, not only does the country variance decrease but also the rank order of the countries changes. The Southern-European countries and Ireland have the highest observed absolute mobility rates, but after error is removed, their relative position drops. On the other hand, countries like Denmark and the UK, which have a relatively low observed mobility rate, have in fact one of the highest true absolute mobility rates. The most extreme case seems to be Italy which has one of the highest observed absolute mobility rates, but the true absolute mobility rate in Italy is one of the lowest.

When re-analysing the true and observed outflow rates in Figure 5.2, this time comparing countries, the first thing that is noticed is that the error corrected outflow rate shows less country variation than the observed outflow rate. Also, a substantial part of the observed outflow seems to be due to error: the true outflow rate is usually clearly lower than its observed counterpart. The over-estimation seems to be even higher with the outflow rate than with the inflow rate. An interesting observation is that the countries that show the biggest over-estimation in the observed inflow rate are not the same countries that show the biggest over-estimation in the observed outflow rate. The observed inflow rate is over-estimated by the most in Greece, Spain and Portugal, but the highest over-estimations in the observed outflow rate can be found in Denmark and in the UK.

Here we can see how inflow and outflow rates relate to the absolute mobility rate and how it is the marginal distributions which determine how inflow and outflow rates shape the absolute mobility rate. For example, a poverty classification usually identifies 10–20 per cent of the population as poor. The outflow rate describes what the probability is of someone coming out of poverty. Since the outflow determines the mobility of just a 10–20 per cent minority of the population, error in the outflow rate does not cause a large error in the absolute mobility rate. However, error in the inflow rate causes much larger error in absolute mobility, because the inflow rate determines the mobility of 80–90 per cent majority of the population. This association between absolute mobility, transition probabilities and marginal distributions can also be seen here. Countries that have a high inflow rate also have a higher level of absolute mobility, while there is not this kind of positive association between the outflow rate and the absolute mobility rate.

Therefore, the rank order between countries seems to be the same with the observed and true fluidity. In other words, countries that are ranked high according their observed outflow or inflow rates tend to be also ranked high according their true inflow and outflow rates. On the other hand, the rank order between countries according to their absolute mobility rate changes somewhat when over-estimation is corrected. However, the true poverty and deprivation fluidity show high affinity between countries, although some individual countries show a small deviation from the common (latent) fluidity model. The deviation from the common pattern of fluidity in these few countries is mainly caused by bigger time-heterogeneity in the transition probabilities. We will now take a theoretical approach to the stochastic process behind our transition tables with the aim of explaining the finding that (true) poverty fluidity seems to be surprisingly similar between countries, which at the same time have very different cross-sectional poverty rates.

6.3 Variation in poverty rate, affinity in mobility: an explanation

We have learnt that error also affects marginal distributions, indicating that cross-sectional poverty and deprivation estimates can also contain error. Therefore we must ask, how much the error corrected poverty (and deprivation) rates differ from the observed rates. Is the explanation as to why poverty rates vary between countries while poverty dynamics are common simply that the country variation in poverty rates is due to error that operates on a different level in different countries? Table 6.2 presents error corrected financial poverty, housing deprivation and subjective deprivation rates in the first wave, their means and the standard error of the mean (SE). The error corrected rates are calculated from the parameter estimates of the Latent Mover-Stayer models (products of π and δ are summed over the movers and stayers chains in tables 4.2.2, 4.3.2 and 4.4.2). The error corrected rate follows the observed rate quite closely and large over- or under-estimations in the observer rate are rare.[23] The observed financial poverty rate has a higher mean in the first wave (17.7) than the error corrected rate (17.1). The mean of observed deprivation rate is 19.5 and it is lower than the mean of the corrected rate, 21.3. The mean of observed subjective deprivation rate is 26.0, which is also lower than the mean of corrected rate, 28.9. When comparing the SE of the error corrected rates to the SE of the observed rates, we can see that correcting error does not reduce the country variation. On the contrary, the corrected poverty rates have higher SE than the observed rates for all three indicators. The SE of the observed financial poverty rate is 1.45 compared to the error corrected SE of 1.65, the SE of the observed housing deprivation rate is 3.36 compared to the error corrected SE of 3.53 and the SE of the observed subjective deprivation rate is 4.53 compared to the error corrected SE of 5.21. Hence, countries have large differences in their cross-sectional poverty rates and removing error from these estimates even slightly increases the variation between countries.

Another well-known static poverty estimate and Eurostat's structural indicator is the persistent financial poverty rate, which attempts to measure the quality (persistency) of poverty.[24] We could expect that error would have a larger effect on the persistent poverty rate than on the financial poverty rate, since the persistent poverty indicator is constructed from four repeated financial poverty classifications.

[23] The only exception seems to be Spain which has an exceptionally high over-estimation in the observed financial poverty rate and an exceptionally high under-estimation in the observed subjective poverty rate.

[24] Persistent poverty rate is the proportion of those currently in financial poverty that have been in the same situation for at least two out of the preceding three years (Eurostat 2003). The observed persistent poverty rates are estimated from the frequencies of ABCD transition tables. The error corrected persistent poverty rates are estimated from the frequencies of latent VWXY transition tables, produced by the latent classification probabilities of the partially Latent Mover-Stayer model (see Appendix A).

TABLE 6.2 True and observed (persistent) poverty and deprivation rates and possible macro-structural determinants of poverty and deprivation dynamics

	True Fin.Pov.	Obs. Fin.Pov.	True Depr.	Obs. Depr.	True Subj.	Obs. Subj.	True Pers.	Obs. Pers.	S80/ S20	Un-employm.	Fem. Lab.F.	Soc.Ex. /GDP
DK	11,0	8,9	16,1	9,9	14,5	16,0	7,3	3,7	3,2	6,5	74,1	30,5
NL	14,4	11,0	8,9	9,6	13,6	13,6	10,8	6,0	3,8	6,0	58,3	29,4
B	13,8	18,0	14,8	14,8	18,4	14,0	9,0	10,2	4,6	12,7	56,5	28,1
F	16,5	17,1	28,0	20,0	26,0	19,0	12,0	10,9	5,7	12,3	59,9	30,8
UK	19,7	21,0	20,5	16,3	14,8	12,0	13,4	13,2	6,4	8,2	66,4	27,3
IRL	20,6	17,6	15,5	14,0	28,9	32,0	14,8	10,1	4,8	11,1	49,4	17,2
I	18,2	18,7	13,8	15,6	19,2	21,7	13,8	10,7	6,1	12,0	43,8	25,7
E	9,9	19,5	16,3	19,3	54,7	36,9	4,9	9,6	6,1	21,9	46,2	22,0
EL	19,5	21,4	33,6	32,3	55,2	55,1	14,8	14,0	7,6	10,4	47,5	23,6
P	27,6	23,9	45,5	43,6	44,1	39,8	19,0	14,8	8,3	7,1	61,1	22,5
Mean	17,1	17,7	21,3	19,5	28,9	19,5	12,0	10,3				
SE	1,65	1,45	3,53	3,36	5,21	4,53	1,3	1,08				

Source: ECHP; OECD 1998; OECD 2001; Eurostat 2003.

We might expect the persistent poverty rate to have statistical characteristics that resemble both the characteristics of the poverty rate and of poverty dynamics. Table 6.2 shows both the observed and the error corrected persistent (financial) poverty rates for each country. The true persistent poverty rate follows the observed rate in every country, except in Spain where the observed persistent poverty rate seems to vastly over-state the number of persistently poor.[25] It seems that the persistent poverty rate underestimates the proportion of persistently poor, unless error is corrected. The mean of the persistent poverty rate is 10.3 compared to the mean of the error corrected rate of 12.0. The under-estimation of the persistency of poverty is what we expected, knowing that poverty mobility is over-estimated.

So we can conclude that cross-sectional poverty and deprivation rates vary between countries. Removing error even increases the cross-country variance. What macro-structural factors could explain this variance in national poverty (and deprivation) rates? The labour market is the main source of income in every country, so the labour market related characteristics, like unemployment or female labour force participation, might have some power of explanation over the poverty rate. For example, high unemployment figures indicate that a large part of the population has no market income, suggesting a high poverty rate. On the other hand, high female participation in the labour force might suggest a lower poverty rate, since a higher number of families have two earners and this way a 'double buffer' against social risks. Table 6.2 presents the unemployment and female labour force

[25] The Latent Mover-Stayer model does not have a particularly good fit with the Spanish table, so the error corrected estimates for the Spanish panel could be unreliable.

participation rates and it seems that countries that have a high unemployment rate tend to also have a higher poverty rate. But the female labour force participation rate and the poverty rate seem to have no association. We might also expect that the extent and universality of the welfare state would have an effect on the level of poverty. The last column in the table describes the ratio between the national social expenditures and the gross-domestic production and the higher the ratio is, the more extensive we can assume the welfare state of the country to be. There are large differences between countries in their social expenditures to GDP-ratio and countries that have a more extensive welfare state tend to have also a lower poverty rate. But there are exceptions, such as France that has the highest social expenditures to GDP-ratio (30.8), but at the same time an average level of poverty.

It seems that the level of income inequality is the best available explanation to the differences in the countries' poverty rates. The S80/S20 ratio is a simple income inequality indicator that describes how much more the highest income quintile (20 per cent of the population) earns in total compared to the lowest income quintile (see Eurostat 2003). The lowest income inequality according to the S80/S20 ratio can be found in Denmark (3.2), while the highest can be found in Portugal (8.3). The S80/S20 ratio has a clear positive association with the financial poverty rate: countries that have high income inequality tend to also have a high financial poverty rate. This is not surprising since the relative financial poverty measure is a function of the income distribution and the positive association between inequality and financial poverty has been reported in several studies (see Atkinson et al. 1995). What is perhaps more interesting is that the subjective deprivation rate and the housing deprivation rate also seem to have a positive association with the income inequality S80/S20 ratio. We can assume that the subjective deprivation rate and the level of income inequality have a positive association because a minimum standard of living that is felt not to be reached is always in some way related to the average level of living conditions in the society. If the level of inequality is high and visible in the society, the feeling of having too little may arise more readily than in a more equal society. But the positive association between the S80/S20 ratio and the housing deprivation rate cannot be explained by socio-psychological factors, since the deprivation measure is supposed to be an objective measure.

We might have expected these macro-structural factors that seem to cause differences in the static poverty and deprivation estimates to also cause country variance in poverty mobility by shaping, at least partially, the patterns of flows into and out of poverty. For example, we might have expected that an extensive and universal welfare state would decrease the inflow into poverty by hedging people against sudden market impacts and other social risks. Or we might have expected high female participation in the labour market to decrease the inflow into poverty, because two-earner families have a 'dual-buffer' against social risks, or that high unemployment would cause difficulty in exiting poverty and this way decrease poverty mobility. We could also hypothesise that income equality could have a positive association with poverty mobility, since in a more equal income distribution the average distance from a poverty threshold is short, which makes crossing the poverty threshold easier for the majority. We could have hypothesised that the flexibility of the labour market can influence how easy it is for those at risk of moving between poverty and non-poverty to do so. We could have used these macro-structural factors to explain differences in poverty mobility, as we explained the differences in poverty rates, but as we already know, there is no variance in relative poverty mobility to be explained. There are differences in absolute mobility rates, but the transition probabilities are very similar across countries and indicators. What needs to be explained are not the expected differences in relative poverty mobility, but the affinity discovered between the countries.

The explanation of the affinity in poverty and deprivation fluidity is perhaps quite simple. The reason why the (Latent) Common Fluidity model has such a good fit to the data might be simply that the model allows marginal distributions to be estimated freely at every measurement point. It could be that when marginal distributions are estimated freely, the parameter estimates of transition probabilities are not so significant. When each marginal distribution is fitted perfectly in the model, the Markovian process and the convergence towards equilibrium is interrupted after each transition step. A Markovian process converts rapidly towards equilibrium from any (marginal) initial value and the equilibrium value is extremely sensitive to even small changes in the transition probabilities. In other words, a Markovian process can produce very different marginal distributions, or cross-sectional rates, with only slightly different transition probabilities.

The ability of the Markovian process to convert marginal distributions towards an equilibrium value can be utilised for predicting what the poverty rate (i.e. marginal distribution) will be in time *t+1*. The equilibrium value α for a pair of inflow and outflow probabilities can be calculated as (taken that inflow and outflow are time-homogeneous):

$$\alpha \ = P_{\inf low}(P_{\inf low} / P_{outflow}) \qquad [6\text{-}3]$$

In a single step a time-homogeneous first-order Markovian process converts towards an equilibrium value α from any initial starting value according to the equation:

$$\alpha_{t+1} = P_{\inf low}(1-\alpha_t) + \alpha_t(1-P_{outflow}) \qquad [6\text{-}4]$$

where α_t is now the initial poverty rate (marginal distribution) in time *t*, α_{t+1} the marginal distribution in time *t+1* and *P*'s the transition probabilities of inflow and outflow. The equation 6-4 converts into an (near) equilibrium in 10 to 15 transition steps, or iteration rounds. For example, the pattern of fluidity that has the inflow rate of .04 and the outflow rate of .12 converges to an equilibrium alpha value of .25, which is the same value as the highest observed financial poverty rate in our data. The equilibrium value is very sensitive to the changes in inflow and outflow rates, especially to changes in inflow rates, since the inflow rate (in our data) applies to the majority of the population. For example, lowering the inflow rate from .04 to .03 lowers the alpha value to .20. On the other hand, increasing the outflow rate from .12 to .13 (and keeping the inflow rate at .04), decreases the equilibrium value only from .25 to .24. The lowest observed financial poverty rate in our data is roughly 10 per cent. Taken as an equilibrium, this value can be reached with a pair of inflow and outflow rates of .02 and .18, for example. So we can see that the (simple) Markovian process can produce the highest and the lowest financial poverty rate in our data, 10 and 25 per cent, with only slightly different pairs of inflow and outflow rates; .02/.18 and .04/.12. Hence, it is not surprising that the pattern of fluidity seems so common between countries in Figures 5.2 and 5.3.

6.4 Conclusions

The answer to the fourth research hypothesis is confirmative: there seems to be a common pattern of poverty fluidity between countries. We have reached this conclusion by fitting the Latent Common Fluidity model to the layered transition tables of financial poverty, housing deprivation and subjective deprivation. The Latent Common Fluidity model allows marginal distributions, i.e. poverty and deprivation rates, to vary across countries, but assumes that the pattern of transition probabilities is common across the countries. The misclassification of the model was 2.3 per cent in the layered financial poverty transition table, 2.2 per cent in the housing deprivation and 2.7 per cent in the layered subjective deprivation table. A closer examination revealed that the Spanish table caused the largest mismatch between the model and the data. Almost half of the total likelihood ratio value under the model came from the Spanish sub-table in the financial poverty table and a quarter in the deprivation and subjective deprivation tables. The (latent) fluidity is more time-heterogeneous in the Spanish sub-table than in other country-layers, which explains most of the mismatch. Taking into account the fact that we are modelling a layered transition table with exceptionally high Ns, we can say that the model assuming common latent fluidity fits reasonable well with the data. The pattern of true fluidity shows remarkable affinity across all the countries with direct, indirect and subjective indicators. This confirms the preliminary interpretation we made in chapter four (see tables 4.2.3, 4.3.3 and 4.4.3) about affinity in error corrected transition rates.

The (true) poverty and deprivation fluidity has a surprisingly high level of affinity between countries that show large differences in cross-sectional poverty deprivation rates. Similar results have also been reported in other recent studies on poverty dynamics (see Layte & Whelan 2003). An explanation for why poverty and deprivation fluidity shows affinity while the national poverty rates vary might be the fact that very small differences in the transition probabilities can give rise to big differences in the marginal distributions. In other words, a Markovian process can produce very different cross-sectional poverty rates with only slight differences in the pairs of inflow and outflow rates.

A common fluidity also means that we cannot group countries into poverty mobility regimes, similar to the way that countries are often grouped into welfare state regimes, for example. To form regimes based on poverty, this has to be done according the static estimates. Countries can be grouped into regimes according to their poverty and deprivation rates (observed or error corrected) and these regimes would be well matched to the four established welfare state regimes. But both the level of mobility (i.e. absolute mobility) and the pattern of mobility (i.e. fluidity) show a high affinity across all the countries, especially after error is corrected from the estimates of poverty mobility.

7 Conclusions

7.1 Introduction

We have compared countries and indicators, observed and error corrected estimates. However, not all of the findings of the study have been produced by comparative methods. One of the main findings of the study, i.e. that poverty and deprivation dynamics can be described by the classical Mover-Stayer model, was a result of tenacious log-linear model building. The result of this model building reconciled the two seemingly contradictory characteristics of poverty dynamics that have confused researchers: the high level of poverty mobility together with very persistent and long poverty spells. We showed that there are two types of poor: those living in constant poverty and those who experience frequent but short poverty spells. Only through longitudinal analysis are we able to identify these two groups that would have remained invisible to static snapshots. When the absolute and relative aspects of poverty (and deprivation) mobility were analysed separately, the comparative method also revealed some other unknown characteristics of poverty dynamics. Based on classical test theory we expected that random error would cause some over-estimation in the panel data, but error was discovered to operate in a more complex way across countries and indicators than was first assumed. Also our assumptions about country differences in absolute mobility and fluidity had to be thoroughly reassessed during the empirical analyses.

But how do these findings fit with previous studies and theories of poverty and poverty dynamics? Is the longitudinal structure containing movers and stayers generalisable as the general structure of social disadvantages? And from where does the longitudinal structure of poverty arise and how? Are there any policy recommendations that this study could generate? These are the questions that this summary chapter seeks to answer by drawing together the empirical findings of the study and interpreting them in a larger context, and finally, pondering upon some policy recommendations from the results. In section two, the empirical findings of the study are first summarised and then considered in the light of the previous studies and existing theories. In the third section, we look at how this altered view of poverty from static to dynamic changes our understanding about this multidimensional phenomenon and how the dynamic approach might influence social policy and perhaps provide new tools for policy makers. Some old and some new conceptual and theoretical building blocks are proposed on how poverty could, and should, be understood as a temporal and dynamic phenomenon instead of as a static condition. However, not only are the advantages of a dynamic approach highlighted but also the possible dangers attached to the dynamic approach.

7.2 Summary of empirical findings

We have studied two aspects of longitudinal poverty in this study; the distribution of poverty spells in the population and the likelihood of future poverty spells. Much less attention is given to the third aspect of longitudinal poverty, which is the duration of poverty (see Jäntti & Danziger 2000). Naturally this distinction is more of an analytical one, since the duration depends on the transition probabilities.[26] There is also dependence between absolute mobility, transition probabilities and marginal distributions, as we have seen. Poverty rate and poverty mobility are the two sides of the same coin. The current poverty rate is 'produced' by the past mobility, where people have moved to, or stayed in, their present poverty status. How many moves, and where, is shaped by the proportions of poor and non-poor (i.e. marginal distribution) and the inflow and outflow probabilities, which then determine the level of absolute mobility.

The direct, indirect and subjective poverty indicators that are used in this study are assumed to measure different dimensions, or manifestations, of poverty. Poverty is seen as an abstract social concept and essentially a non-Platonic measurement object. Costner (1969) and Blalock (1968) emphasised that we should always remember three things when measuring abstract concepts in sociology. First, we must evaluate whether the empirical measurements are adequate and valid indicators for measuring the abstract formulation. Second, we must evaluate whether the abstract formulation itself is tenable. Thirdly, we must build a theory that explains why these two components, the indicator and the concept, relate to each other in the way they do. The abstract formulation that we attempted to measure here is Townsend's definition on poverty as relative deprivation. The measurements that are used as the indicators of poverty are financial poverty, housing deprivation and subjective deprivation head-count measures.

The chronological order in this study has meant that the dynamics of poverty are first modelled and then compared across poverty measures and countries. This is also a good order to present the empirical results of the study. In chapter three we presented four research hypotheses that were tested against the ECHP panel data. Each hypothesis was derived from an earlier theory or thesis.

The first research hypothesis states that the population is heterogeneous in their relation to the transition of poverty. This hypothesis is derived from the individualisation thesis that says that in the affluent welfare states, poverty is connected more to individual biography and life-situation than to social class structure or stratification in general. This suggests that poverty is no longer only a problem for a clear-cut fragment of the society, instead, poverty also touches the middle classes in the contemporary welfare states (see Leisering & Leibfried 1999).

[26] The expected duration of poverty, for example, is equal to 1/(probability to exit poverty) if transition probabilities are time homogeneous (Cox & Miller 1965, 135–9).

If the individualisation thesis is true, poverty incidences should be transitory and distributed quite equally across the population. We can interpret from this that the more equally poverty incidences are distributed across the population, the more people there are experiencing short poverty spells and the less people there are experiencing persistent poverty. On the other hand, poverty can be seen to be completely structural if there are only two groups of people in the population; always poor and never poor. By studying the dynamics of poverty we are given the possibility to test the individualisation thesis, although superficially.

The descriptive figures of poverty and deprivation dynamics indicated that the population can be divided into stayers and movers and that the risk of poverty (or deprivation) re-occurring remains high for years. We expected that a model that would describe this kind of dynamic process would be found in the family of Markov models. After tenaciously fitting models we found a Markov model that was able to explain the dynamics of poverty in every transition table. The final model was the Latent Mover-Stayer model, which contains the structural sub-model and the measurement sub-model. The structural sub-model (i.e. the causal model) assumes that the population is divided into movers and stayers. The stayers either stay in poverty or stay out of poverty and the movers move in and out of poverty following the simple Markovian process. The measurement sub-model relates every observed (i.e. manifest) measurement to its structural counterpart variable by probabilistic relationship, allowing a separate error for each manifest measurement among the movers but assuming that the stayers are measured without error.

The parameter estimates of the Latent Mover-Stayer model indicate that around half of the population or more can be considered as movers, depending on the country and what poverty indicator is used. The finding that the majority lives with a risk of short poverty spells is congruent with the individualisation thesis that states that contemporary poverty even impinges on the middle classes. On the other hand, we can see that the other half of the population are stayers, either staying constantly in poverty or always staying out of poverty, which points away from the individualisation thesis. The vast majority of stayers are non-poor, but the proportion of people who are constantly poor is relatively high in some countries. Countries that have a high cross-sectional poverty rate tend to also have a relatively high section of the population who are constantly poor. The high proportion of stayers, either never in poverty or always in poverty, suggests that poverty is still very much a structural phenomenon. Poverty is a stable condition for a clear-cut, though small, fragment of the population, while a large part of the population never experience poverty.

However, the general longitudinal structure of poverty and deprivation that we have discovered is not congruent with hypotheses that in the affluent welfare state poverty has become transient and transcendent over social boundaries, as the individualisation thesis argues (Leisering & Leibfried 1999, 239). Poverty and deprivation spells seem to be recurrent rather than transient and the risk of poverty or deprivation is very unequally distributed in the population. These findings are congruent with the result of Layte and Whelan (2002), also Andreb and Schulte (1998). However, we cannot give a definite answer to the question of whether poverty has become just an episode in the course of life as the individualisation thesis also states. We have followed people for only a relatively short period of time and to be able to test satisfactorily the claim that poverty has become 'biographised', we would need data covering a much longer period, preferably the whole life span of the studied people. With the data in our use, the only thing that we can safely conclude is that the population is heterogeneous in their relation to the transition of poverty and that the population can be divided into three groups that have very different, and permanent, poverty trajectories. The discovery of these three groups gives support to the typology of poverty profiles developed by Fouarge and Layte (2003) to examine the persistence and recurrence of poverty.

The same longitudinal structure that emerges in every country and with every indicator indicates that the same macro-structural factors shape the longitudinal structure of poverty and deprivation. Sometimes the importance of sociological phenomena lies in its constancy, not in its variance, and we should try to find explanation for this constancy in the same way as we would seek to explain the variance (see Erikson & Goldthorpe 1992, 389–391). The structure of social stratification arises from the different positions in the production system, which is still the main source of income and wealth (ibid., 35–47, see also chapter 1.2.2.). So we can assume that also the structure of disadvantages arises from the different positions in the production system, though heavily shaped by the welfare state and family institutions (see Layte et al. 2001, see also chapter 1.4). There are authors who suggest that large, even qualitative, changes have taken place in the economy and society in the last decades (e.g. Castells 1996). Changes in the labour market and in the society in general (increased use of self- and fixed-term employment, the expansion of tertiary education and following prolonged time in education and the increased average-age for having children) have changed the nature and distribution of positions in the production system.

The relatively large proportion of movers in every country indicates that a large part of the population do not hold permanent positions in the labour market and that the welfare state with its redistributive institutions is partly inadequate in preventing the economic consequences of the precariousness in the labour market. The model where the structure of disadvantages arises from the allocation of positions in the labour market and is shaped by the family and the institutional arrangements of welfare state would explain both the common longitudinal structure of poverty and the variation in the relative sizes of movers and stayers inside this structure. Ten EU countries that are studied here have similar production systems based on a market economy, similar family structures based (mainly) on the nuclear family and similar institutional arrangements for the redistribution and pooling of social risks. Naturally, the ten countries have differences in their labour markets, family structures and welfare state arrangements. But these three institutions are found in every country studied (as in every western industrialised country), which probably explains why the longitudinal structure of disadvantages is similar. The differences between the countries are seen as the variation in the relative sizes of movers and stayers. However, clarifying the relationship between, and changes within, the structure of disadvantages, the labour market, the welfare state and family need more empirical and theoretical work.

The second research hypothesis states that mobility in the poverty transition table is over-estimated if random error is ignored. This hypothesis is based on empirical studies that have shown that error causes under-estimation of stable cases in panel data (e.g. Hagenaars 1992; Breen & Moisio 2004). The Latent Mover-Stayer model can be used to estimate the true stability and error in a discrete time and space panel data, as Langeheine and van de Pol (1990) showed. The error corrected estimates show that both the absolute as well as the relative poverty and deprivation mobility (fluidity) is over-estimated if random error is ignored, so our hypothesis was confirmed. Absolute poverty and deprivation mobility especially seem to be vastly over-estimated, by 25 to 50 per cent, if random error is not taken into account. Poverty fluidity is also over-estimated, especially the outflow probabilities, if error is ignored. Hence, much of what appears to be exits from poverty (or deprivation) is actually measurement error. The over-estimation in the observed inflow is not as high as in the outflow. The reliability matrices of the measurement-sub model show that the error is mainly associated with the failure to accurately identify the poor, the non-poor are identified with much less error. Also random errors seem to operate with a differential effect in the various countries. This is most noticeable with the absolute mobility rate which shows a much larger variation between countries before the error is corrected. The over-estimation seems to be particularly large among some Southern-European countries, whose absolute mobility rate dropped dramatically when error was corrected.

The error does not just effect the estimates and comparisons of poverty dynamics, but error also has an effect on the cross-sectional poverty and deprivation rates. The differences between the corrected poverty and deprivation rates and error corrected rates, however, are not that dramatic. However, estimates that somehow incorporate the length or the frequency of poverty spells into the measurement are vulnerable to the same systematic bias as the estimates of absolute and relative mobility. For example, one of the EU social indicators, the persistent poverty indicator incorporates information about the length and frequency of financial poverty spells into the measurement (see Atkinson et al. 2002). As we expected, the indicator under-estimates the number of people in persistent poverty, because random error in the panel data is taken as mobility. It seems that every longitudinal poverty measure gives biased estimates if random error is ignored.

The third research hypothesis states that the pattern of fluidity is common between the three poverty measures. The hypothesis is derived from the thesis presented by Gordon (2002) that the financial poverty and deprivation measures are measuring the same dynamic process, but in its different phases.[27] However, with this set of analysis we cannot test if these three indicators are measuring the same dynamic process - we have only tested if their fluidity patterns are similar. The transition table of financial poverty, housing deprivation and subjective deprivation were combined into one layered table. The Latent Common Fluidity model was fitted to the layered table to test whether there is a common pattern of fluidity across the layers. The Latent Common Fluidity model is again a genuine measurement model that contains a structural sub-model and a measurement sub-model. The structural sub-model assumes that the marginal distributions (i.e. poverty rates) vary between indicators, but the transition probabilities (i.e. fluidity) are common across indicators. The measurement sub-model relates again each manifest measurement to the structural sub-model with probabilistic relationships, allowing each indicator to have a separate error. According to the model fit diagnostics, all three of the poverty indicators have a common pattern of fluidity only in Italy, Denmark, France and the UK. However, financial poverty and housing deprivation have a common pattern of fluidity in every country. So, the hypothesis that financial poverty, housing deprivation as well as economic strain indicators have the same fluidity does get prudent support.

The last research hypothesis states that the poverty fluidity is common between countries. This hypothesis is based on the study of Layte and Whelan (2003), where they found that the poverty transition probabilities are fairly similar across the EU countries. We tested the common pattern of fluidity -hypothesis again with the Latent Common Fluidity model. This time the transition tables were combined across countries and the model was fitted to the layered transition table of financial poverty, housing deprivation and subjective deprivation, each containing ten country layers. The Latent Common Fluidity model allows poverty and deprivation rates to vary across countries, but assumes that the pattern of latent transition probabilities is common. The model has a good fit in all three tables, so the answer to the fourth research hypothesis is yes: there seems to be a common pattern of poverty and deprivation fluidity between countries. We did not make a formal hypothesis about the possible affinity in the absolute mobility rates between countries, but during the analyses we discovered that removing the effect of random error decreases country variation in the absolute mobility rate dramatically. Most

[27] Gordon's thesis suggests also that the dynamics of financial poverty and deprivation are in synchrony in a way that means that deprivation follows financial poverty with a lag. However, we cannot test this thesis with our layered transition tables, so this testing is left for later studies.

of the country variation in the absolute mobility rate are caused by error that is larger in some countries than in others. So the conclusion from the comparison between countries is that the poverty and deprivation fluidity have high affinity across countries. As an explanation as to how fluidity can show affinity between countries that have large differences in their cross-sectional poverty and deprivation rates, we present the fact that very small differences in the transition probabilities can give rise to big differences in marginal distributions. In other words, very different cross-sectional poverty rates can be produced with only slightly different transition probabilities.

So poverty reaches a larger part of the population than the cross-sectional poverty or deprivation rate indicates - a much larger fraction of the population has experienced poverty or deprivation than is living in poverty or deprivation momentarily. This can be detected as high poverty and deprivation mobility. High poverty mobility also means that from those identified as poor momentarily, only a minority is expected to stay in poverty for a long period while the majority is expected to have a transient poverty spell. However, our analyses have shown that these transient poverty spells seem to be concentrated among the same group of people that we have named as poverty movers. The cross-sectional measure identifies those poverty movers that are in poverty at the moment together with the poverty stayers as poor. The existence of these two groups, poverty movers and stayers, explains why poverty seems to be transitory and persistent at the same time, which has given poverty dynamics an ambivalent character. We studied only three head-count measures in ten countries, but we would expect other head-count poverty and deprivation measures to lead to similar results when used in repeated measurements. Also the constancy of the longitudinal structure of poverty (and disadvantages) across countries requires more empirical and theoretical work on the macro-structural factors that shape this structure.

7.3 Recommendations of the study: Changing the view on poverty and policy

The change of perspective of poverty from static to dynamic naturally causes changes in the measurement level. Instead of thinking about how many people are below some poverty threshold at a given moment, the longitudinal perspective looks at how many people live in constant poverty or in a poverty cycle and what events can trigger poverty or can help someone to leave poverty. Hence, with a longitudinal research setting we can study the causes of poverty, not just what the level of poverty is and how poverty is distributed in the society. At the policy level, this would make it possible to treat the causes of poverty, not just the symptoms.

The dynamic approach can enlarge the toolkit of the social policy makers. If we know the events and processes that seem to trigger poverty, policies can be designed to prevent people from entering poverty in the first place. On the contrary, if we know the events and processes that seem to help people to get out of poverty, policies can be designed to support these events and processes. (see Bradbury et. al. 2001, 2–4.)

When starting to think of poverty as a temporal phenomenon that has a beginning and an end, we should bear in mind that the events leading to poverty are not necessarily the same as the events that help exit it. This is actually one of the interesting findings that the studies of poverty dynamics have produced. Changes in household structure, such as divorce or an addition to the family, are often the events that seem to trigger a poverty spell. However, the event that usually helps people to exit poverty is an improved employment situation and therefore an increased income. Nevertheless, a decrease in income, not a demographic change in the household structure, is still the most common reason for entering poverty. However, a change in household structure is often accompanied by a decrease of income due to the decrease in the number of earners in the family, either because of the breaking up of the household or due to maternal leave (e.g. Bane & Ellwood 1986; Jenkins 2000).

The poverty rate of a country is the product of poverty inflows and outflows. In other words, how many people have entered poverty and how many have exited poverty. With the dynamic approach, social policy can be targeted to decrease the inflow into poverty or to increase the outflow out of poverty (or try to do both) and this way lower the number of people in poverty. Changes in the poverty rate can also be studied more closely using inflows and outflows. An increase in the poverty rate, for example, is caused always either by an increase in the inflow into poverty or a decrease in the outflow from poverty, or both. The information of whether it is the change in the inflow or in the outflow that is responsible for the increased poverty rate helps to target the scarce resources to where they are probably the most effective. Additionally, changes in the poverty inflow and outflow rates can provide a tool for making a prudent prediction of how the poverty rate will develop in the near future. Each pair of in- and outflow rates has a certain equilibrium poverty rate towards which they convert the poverty rate.[28] If the poverty rate is not in the equilibrium with the current inflow and outflow, we can expect that the poverty rate will converge toward the equilibrium value. We can estimate what the equilibrium poverty rate is for the current in- and outflow rates and we can expect that the poverty rate will move towards this equilibrium value in the near future, assuming that all the other factors remain the same. In practice this means, for example, that a decrease in the poverty outflow, or an increase in

[28] We showed simple equations to calculate is the poverty rate in the equilibrium with the given inflow and outflow rates in chapter 6, section 3.

the poverty inflow, raises the poverty rate by several years until the poverty rate reaches its new equilibrium. Knowing this, the inflow and outflow rates can provide policy makers guarded, but extremely valuable, information about the possible development of poverty rate in the near future. However, poverty transition rates change over time, as was discovered in chapter four, so these predictions are always precarious.

Perhaps the strongest recommendation that this study can give concerns the use of panel data. This study confirms Duncan's (1997) concern about the consequences of neglecting measurement error in longitudinal poverty estimates and studies. The importance of taking measurement error seriously is growing now as the longitudinal studies and poverty measures are becoming increasingly important in policy making. Longitudinal poverty measures have found their way into the EU structural indicators, for example, which shows the growing influence of longitudinal poverty measures in social policy. It should be generally acknowledged among the poverty researchers that random errors do not nullify each other in the panel data as they do in the cross-sectional data. Instead, random error appears as mobility in panel data if error is not treated properly with a measurement model. Random error in panel data causes poverty mobility to be over-estimated, and consequently, the persistency of poverty is underestimated if random error is ignored.

But the change from a static to a dynamic approach can also cause more fundamental changes at the policy level than just changes in the estimation of longitudinal poverty statistics and enlargement of the social political toolkit in the fight against poverty. As was discussed in the introductory chapter, every policy program against poverty contains an explicit or implicit explanation what poverty is (Townsend 1979, 64). The fundamental difference of the dynamic approach compared to the static approach lies in the methodology of longitudinal studies. This is simple because a longitudinal analysis (usually) needs to follow an individual from one time point to the next. This has two consequences. First, poverty is seen more as an individual characteristic, since we can see that some people move in or out of poverty and some do not. Secondly, when we can isolate the individual or family level factors that lead to poverty, for example unemployment or divorce, this can easily blur the structural factors that are always behind poverty. In other words, the factors that explain the entry into poverty of an individual (or a family) cannot always be generalised to the societal level. Moving into poverty can in many cases be explained by the break up of the family, for example, but marital breakdown does not explain why there is poverty in the society. Hence, the danger in the dynamic approach is that it easily individualises poverty by introducing a list of events that often precede the poverty entry. There is then a danger that these triggering events become viewed as the 'actual causes' of poverty. Also, when we then see that some people escape poverty and some do not, the next question could easily be, what are the individual characteristics that 'cause' these people to remain in persistent poverty. So it seems that the dynamic approach is carrying, at least implicitly, a recommendation for active and targeted policies against poverty.

Active anti-poverty policies have often been advocated by referring to the persistency of poverty. In the United States several studies in the 1980s showed that many recipients of means-tested benefits received the assistance for years. These findings launched a serious welfare reform in the 1990s. The main argument for the reform was that the unconditional social assistance was believed to cause welfare dependence. Motivation to work was believed to be the answer to the problem of poverty. Working or training was made a condition of receiving means-tested benefits. The number of people on welfare dropped dramatically in just a few years after the reform, but it is generally admitted that the activation programs did not alleviate poverty. (see Aber & Elwood 2001, 295.) Instead, the welfare reform increased the number of working poor, although it reduced the number of welfare poor. There is also a danger that a possible failure of activation easily individualises the poverty problem, which has happened to some degree in the United States. So, the experiences of the activation programs for the poor are not very encouraging.

Also, research findings that have indicated that poverty is mainly transitory have been used to criticise exercised social policy. Leisering and Leibfried (1999) studied the recipients of social assistance in Germany and they discovered that the majority of the recipients received assistance for only a short period. They called for a life-course approach to social policy where social risks would be managed through the whole life span of individual (id. 29-33). Hence, Leisering and Leibfried called for a qualitative change to the universal social policy that they saw as poorly targeted and inefficient. It is hard to deny some of their arguments about feebly designed universal social policies, since poverty is usually more common among children than in the rest of the population. This means that social policy is often unable to bend with the changing needs that people have through their life-course. However, it is hard to imagine how an individually tailor-made, life-course social policy would work in practice, since the administrative costs of it would undoubtedly be very high.

It has also been proposed that the high poverty mobility might erode the popularity of universal social policy (Hill & Jenkins 2001). When the policy makers and the public are shown studies where it is revealed that the majority of the poor are in poverty only for a short time, obviously they might start to question, whether the universal social transfers should be targeted and made means-tested. If the most of the poor are actually just 'visiting' poverty for a short period, should we try to target the help towards those who really need the social assistance and not just spread money more widely to the people who really do not need it? This would mean favouring targeted social policy over the universal. However, this study has shown that the estimates of poverty mobility are substantially lower once error is corrected and that high mobility does not mean that the majority of the poor are in poverty for a short spell and then permanently leave. On the contrary, we have learnt that it is generally the same group of people who move in and out of poverty.

But choosing the dynamic approach towards poverty does not necessarily mean that one automatically also has to choose activation and targeted social policies. What the dynamic approach means, at least what we believe, is that we should see poverty in a similar way as, for example, unemployment. Both poverty and unemployment have a beginning, a duration and an end, but only unemployment is usually seen and treated as a dynamic phenomenon at the policy level. Along with social security, most of the welfare states have active employment policies that are aimed to improve employment and reduce unemployment. In other words, welfare states have active employment policy programs that are aimed at increasing the inflow into jobs and decreasing the outflow from jobs. The means of active employment policies vary from the subsidised employment to education and training. Education and training programs are usually aimed at improving the professional skills of the entire workforce, not just those who are unemployed. On the contrary, when the problem of poverty is brought up as an issue in a policy debate, the emphasis is often only in the insufficiency of social assistance: how much more money would be needed to get the poor above the poverty threshold, not so much on how we could prevent people from falling into poverty in the first place. However, a distinction between employment and poverty policies is not necessarily easy to make, since in many cases a good employment policy is (seen as) the best anti-poverty policy. This is obvious since the problem of gaining sufficient earnings in the labour market can be seen as the main cause of poverty. In the welfare states that practise universal social policy, it is especially difficult to isolate a specific policy area that could be called the anti-poverty policy. Tailor-made anti-poverty programs tend to be more common in the welfare states that practice more residual social policy. Universal social policy is supposed to deal with poverty in the whole range of policy.

Perhaps universal social policy provides the best conditions for utilising the full potential of the dynamic approach. Longitudinal poverty studies can shed light on the larger mechanisms in the society that cause poverty, mechanisms that are often beyond the sight and scope of traditional social policy. For example, we are finally starting to realise, or admit, how the prolonged education, precarious employment and the determination rules of the maternity leave benefits form conditions where addition to the family is likely to trigger a poverty spell. With longitudinal poverty studies we can follow individual paths into poverty and this way reveal these mechanisms and events that seem to trigger a poverty spell. Changing these macro-structural mechanisms and protecting families from the events that trigger poverty would require cooperation between different policy areas – in this case, coordination between education, the labour market and social policies. Each of these policy areas has its own historical development and goals and they may be unaware of the consequences of their possible synergism.

This study is not designed and cannot give an unambiguous answer to the question of what kind of policies should be used for the fight against poverty. The main advantage that follows from the dynamic approach is the richer and more truthful picture of the multidimensional and temporal phenomenon called poverty. The poverty rate is a rough snapshot that does not correspond to our understanding of poverty as a temporal phenomenon that has a beginning, a duration and an end. The dynamic approach towards poverty also gives a larger variety of tools to social policy makers in their fight against poverty when the events and processes that either trigger or end poverty spells are revealed. In this way social policy makers can try to treat the causes of poverty, not just the symptoms.

REFERENCES

Aber L. J. & Ellwood, D. T. (2001): Thinking about children in time *in* The Dynamics of Child Poverty in Industrialised Countries (eds. Bradbury, B. & Jenkins, S. P. & Micklewright, J.). Cambridge University Press. pp. 281–300.

Agresti, A. (1990): Categorical data analysis. John Wiley & Sons, New York.

Alcock, P. (1993): Understanding Poverty. MacMillan, London.

Andreb, H.-J. & Schulte, K. (1998): Poverty risks and the life cycle: The individualisation thesis reconsidered *in* Empirical Poverty Research in Comparative Perspective (ed. Andreb, H.-J.) Aldershot: Ashgate.

Andrich, D. (1988): Rasch Models for Measurement. Sage University Paper series on Quantitative Applications in the Social Sciences. Sage, Beverly Hills.

Atkinson, A. B., Rainwater, L. and Smeeding, T. M. (1995) Income Distribution in OECD Countries, OECD Social Policy Studies No. 18, OECD, Paris.

Atkinson, A. B. (1995): Incomes and the Welfare State. Essays on Britain and Europe. Cambridge University Press.

Atkinson, A. B. (1998). Poverty in Europe. Oxford: Blackwell Publishers.

Atkinson, A. B. & Bourguignon, F. (2000): Handbook of income distribution. Amsterdam Elsevier.

Atkinson, T. & Cantillon, B. & Marlier, E. & Nolan, B. (2002) Social Indicators: The EU and Social Inclusion. Oxford University Press, Oxford.

Bane, M. J. & Ellwood, D. T. (1986), Slipping into and Out of Poverty: The Dynamics of Spells. *Journal of Human Resources* 21, pp. 1–23.

Bane, M. J. & Ellwood, D. T. (1994): Welfare realities: From rhetoric to reform. Cambrigde, MA. Harward University Press.

Bartholomew, D.J. (1987): Latent variable models and factor analysis. Charles Griffin, London.

Biemer, P. & Stokes, S. L. (1991): Approaches to the modelling of measurement error *in* Measurement Errors in Survey (eds. Biemer, P. & Groves, R. M., Lyberg, L. E., Mathiowetz, N. A. & Sundman, S.). New York: John Wiley & Sons. pp. 487–516.

Bishop, R. J., Fienberg, S. E., & Holland, P. W. (1975). Discrete multivariate analysis: theory and practice. Cambridge, Mass.: MIT Press.

Beck, U. (1994): The Reinvention of Politics: Towards a Theory of Reflexive Modernisation *in* Beck et al. 1994, pp. 1–55.

Beck, U., Giddens, A. & Lash, S. (1994): Reflexive modernisation: politics, tradition and aesthetics in the modern social order. Polity Press, Oxford.

Berghman, J. (1995). Social exclusion in Europe: policy context and analytical framework *in* Beyond the threshold: The measurement and analysis of social exclusion (ed. Room, G.), Bristol: The Policy Press, pp. 10–28.

Blalock, H. M. (1968): The Measurement Problem: A Gap between the Language of Theory and Research *in* Methodology in Social Research (eds. Blalock, H. M. Jr. & Blalock, A. B.) New York: McGraw-Hill. pp. 428–478.

Bollen, K. A. (1989): Structural Equations with Latent Variables. John Wiley & Sons, Inc. New York.

Bourguignon, F. & Chakravarty, S. R. (2003): The measurement of multidimensional poverty. *Journal of Economic Inequality* 1: 25–49.

Bradbury, B., Jenkins, S. P. & Micklewright, J. (2001): The Dynamics of Child Poverty in Industrialised Countries. Cambridge University Press.

Breen, R. & Jonsson, J. (1997): How reliable are studies of social mobility? An investigation into the consequences of unreliability in measures of social class *in* Research in Social Stratification and Mobility Vol. 15. JAI Press, Greenwich: Connecticut. pp. 91–112.

Breen, R. (2000): Why is Support for Extreme Parties Underestimated by Surveys? A Latent Class Analysis. *British Journal of Political Science* 30:2, pp. 375–382.

Breen, R. (2002): Foundations of Class Analysis in the Weberian Tradition *In* Alternative Foundations of Class Analysis (ed. Wright E. O). <URL> http://www.ssc.wisc.edu/~wright/Found-all.pdf (26.8.03). pp. 41–69.

Breen, R. & Moisio, P. (2004): Poverty dynamics corrected for measurement error. *Journal of Economic Inequality*. (forthcoming)

Castells, M. (1996): The Rice of the Network Society. Blackwell Publishers Ltd, Oxford.

Citro, C. F. & Michael, R. T. (1995): Measuring Poverty. A New Approach. National Academy Press, Washington D.C.

Chua, T. C. & Fuller, W. A. (1987): A Model for Multinomial Response Error Applied to Labor Flows. *Journal of the American Statistical Association* 82, pp. 46–51.

Coleman, J. S. (1968): The mathematical study of change *in* Methodology in Social Research (eds. Blalock, H. M. Jr. & Blalock, A. B.) New York: McGraw-Hill. pp. 428–478.

Coser, L. (1965): The sociology of poverty. *Social Problems* 13:2, pp. 140–148.

Costner, H. L. (1969): Theory, Deduction, and Rules of Correspondence. *American Journal of Sociology* 75:2, pp. 245–263.

Cox, D. R. & Miller, H. D. (1965): The Theory of Stochastic Processes. Chapman & Hall, London.

Creedy, J. (1998): The Dynamics of Inequality and Poverty. Comparing Income Distributions. Edward Elgar, Cheltenham.

Davis, K. & Moore, W. E. (1945): Some Principles of Stratification. *American Sociological Review* 10, pp. 242–249.

Del Boca, F. & Darkes, J. (2003): The validity of self-reports of alcohol consumption: state of the science and challenges for research. *Addiction* 92 (suppl.2), pp. 1–12.

Dempster, A. P., Laird N. M. & Rubin D. B. (1977): Maximin Likelihood from Incomplete Data via the EM Algorith. *Journal of the Royal Statistical Society.* Series B, Vol. 39:1, pp. 1–38.

Donnison, D. (1988): Defining and Measuring Poverty: A Reply to Stein Ringen. *Journal of Social Policy* 17:3, pp. 367–374.

Duncan, G. (1984) Years of Poverty, Years of Plenty. Ann Arbor; Institute for Social Research, University of Michigan.

Duncan G., Gustafsson, B., Hauser, R., Schmaus, G., Messinger, H., Muffels, R., Nolan, B. & Ray, J.: (1993): Poverty Dynamics in eight countries. *Journal of Population Economics* 6, pp. 215–34.

Duncan, G. J. (1997) Household Panel Surveys: Prospects and Problems *in* Household Panel Studies: Methods and Substance (ed. Rose, D.). University College London Press, London.

Epunet (2003): Epunet: Connecting ECHP Users. <URL> http://epunet.essex.ac.uk (15.10.2003)

Eurostat (1994): European Community Household Panel. Tracing for the Second Wave of the ECHP. PAN 27/94. Eurostat, Luxembourg.

Eurostat (1997): Response rates for the first three waves of the ECHP. PAN 92/97. Eurostat, Luxembourg.

Eurostat (1998): Social Portrait of Europe. Eurostat, Luxembourg.

Eurostat (2003): Structural Indicators. <URL> http://europa.eu.int/comm/eurostat (1.9.2003)

Erikson, R. & Goldthorpe, J. H. (1992): The Constant Flux. A Study of Class Mobility in Industrial Societies. Oxford, Clarendon Press.

Esping-Andersen, G. (1990). The Three Worlds of Welfare of Capitalism. Princeton: Princeton University Press.

Fisher, G. M. (1992): The Development and History of the Poverty Thresholds. *Social Security Bulletin* 55:4, pp. 3–14.

Foster, J. E., Greer, J. & Thorbecke, E. (1984): A Class of Decomposable Poverty Measures. *Econometrica* 52, pp. 761–6.

Fouarge, D. & Muffels, R. (2000): Persistent Poverty in the Netherlands, Germany and the UK. A Model-Based Approach Using Panel Data for the 1990s. EPAG working paper 2000-15. Colchester: University of Essex.

Fouarge, D. & Layte, R. (2003): Duration of Poverty Spells in Europe. EPAG working paper 2003-47. Colchester: University of Essex.

Fritzell, J. (1990): The Dynamics of Income Distribution: Economic Mobility in Sweden in Comparison with the United States. *Social Science Research* 19, pp. 17–46.

Ghiselli, E. E., Campbell, J. P. & Zedeck, S. (1981): Measurement Theory for the Behavioral Sciences. Freeman and Company, San Francisco.

Goldthorpe, J. H. (2000): On Sociology. Numbers, Narratives, and the Integration of Research and Theory. Oxford University Press. Oxford.

Goodin, R., Heady, B., Muffels, R. & Dirven, H.-J. (1999) The real worlds of welfare capitalism, Cambridge: Cambridge University Press.

Goodmam, L. A. (1974a) The Analysis of Systems of Qualitative Variables When Some of the Variables Are Unobservable. Part I – A Modified Latent Structure Approach. *American Journal of Sociology* 79:5, pp. 1179–1259.

Goodmam, L. A. (1974b) Exploratory latent structure analysis using both identifiable and unidentifiable models. *Biometrika* 61:2, pp. 215–31.

Goodman, L. A.(1978): Analyzing Qualitative/ Categorical Data. Abt Books, Cambridge.

Goodman, L. A. (1979). Simple models for the analysis of association in cross-classifications having ordered categories. *Journal of the American Statistical Association* 74, pp. 537–552.

Gordon, D. & Townsend, P. (2000): Breadline Europe. The measurement of poverty. The Policy Press. Bristol.

Gordon, D. (2002): Measuring Poverty and Social Exclusion in Britain. The dynamics of Poverty Workshop, Central European University, Budapest, May 24–25, 2002.

Gouldner A.W. (1970): The Coming Crisis of Western Sociology. Basic Books, New York.

Groves, R. M. (1991): Measurement error across the disciplines *in* Measurement Errors in Survey (eds. Biemer, P., Groves, R. M., Lyberg, L. E., Mathiowetz, N. A. & Sundman, S.). New York: John Wiley & Sons. pp. 1–25.

Hagenaars, A. J. M. (1986): The Perception of Poverty. North-Holland. Amsterdam.

Hagenaars, J. A. (1992): Exemplifying Longitudinal Log-linear Analysis with Latent Variables *in*

Statistical Modelling (eds. van der Heijden, P. G. M., Jansen, W., Francis, B. & Seeber, G. U. H.). Amsterdam: North-Holland, pp. 105–120.

Halleröd, B. (1995): The truly poor. Direct and indirect consensual measurement of poverty in Sweden. *Journal of European Social Policy* 5:2, pp. 111–129.

Hansen, E. J. (1987): Inequality in the Welfare State *in* The Scandinavian Model (eds. Erikson, R., Hansen, E. J. & Ringen, S. & Uusitalo, H.) Me.E. Sharpe, Inc. New York, pp. 109–121.

Heikkilä, M. & Sihvo, T. (1997): Concept of Poverty and exclusion in Europe. *Scandinavian Journal of Social Welfare* 1997:6, pp. 119–126.

Heinen, T. (1996): Latent Class and Discrete Latent Trait Models. Similarities and Differences. Saga, London.

Heise, D. R. (1969): Separating Reliability and Stability in Test-Retest Correlation. *American Sociological Review* 34:1, pp. 93–101.

Henry, N. W. (1973): Measurement models for continuous and discrete variables *in* Structural Equation Models in the Social Sciences (ed. Goldberger, A. S. & Duncan, O. D.). New York, Seminar.

Hill, M. S. (1981): Some Dynamic Aspects of Poverty *in* 5000 American Families: Patterns of Economic Progress: Vol.9, (eds. Hill, M. S. & Hill, D. H. & Morgan, J. N.). Institute for Social Research, Ann Arbor, pp. 93–120.

Hill, M. S. & Jenkins, S. P. (2001): Poverty among British children: chronic or transitory? *in* The Dynamics of Child Poverty in Industrialised Countries (eds. Bradbury, B., Jenkins, S. P. & Micklewright, J.). Cambridge University Press, pp. 174–95.

Jeandidier, B. & Kop, J.-L. (1998): The convergence between different measures of poverty in a static versus dynamic perspective: An empirical illustration in France *in* Empirical Poverty Research in Comparative Perspective (ed. Andreb, H.-J.), Ashgate, Aldershot, pp. 205–226.

Jenkins, S. P. (1991): Poverty Measurement and the Within-Household Distribution: Agenda for Action. *Journal of Social Policy* 20:4, pp. 457–483.

Jenkins, S. P. (2000): Modelling household income dynamics. *Journal of Population Economics* 13, pp. 529–67.

Jäntti, M. & Danziger, S. (2000): Income poverty in Advanced Countries *in* Handbook of Income Distribution. (eds. Atkinson, A. B. & Bourguignon, F.). Amsterdam Elsevier, pp. 309–378.

Jöreskog, J. G.(1969): A general approach to confirmatory maximum likelihood factor analysis. *Psychometrica* 34, pp. 183–202.

Kangas, O. & Ritakallio, V. M. (1998): Different methods-different results? Approaches to Multidimensional Poverty *in* Empirical Poverty Research in Comparative Perspective (ed. Andreb, H.-J.) Ashgate, Aldershot, pp. 167–203.

Kangas, O. & Palme, J. (2000): Does Social Policy Matter? Poverty Cycles in OECD Countries. *International Journal of Health Services* 30:2, pp. 335–352.

Krause, P. (1998): Low income dynamics in Unified Germany *in* The Dynamics of Modern Society. Poverty, policy and welfare *(eds.* Leisering, L. & Walker, R.). The Policy Press. Bristol. pp. 161–180.

Langeheine, R. & van de Pol, F. (1990): A Unifying Framework for Markov Modelling in Discrete Space and Discrete Time. *Sociological Methods and Research* 18, pp. 416–441.

Layte, R., Whelan, C. T., Maître, B. & Nolan, B. (2001): Explaining Levels of Deprivation in the European Union. *Acta Sociologica* 44, pp. 105–121.

Layte, R. & Whelan, C. T. (2002): Cumulative disadvantage or Individualization? A Comparative Analysis of Poverty Risk and Incidence. *European Societies* 4:2, pp. 209–233.

Layte, R. & Whelan, C. T. (2003): Moving in and Out of Poverty. *European Societies* 5:2, pp. 167–191.

Lazarsfeld, P. F. & Henry, N. W. (1968): Latent structure analysis. Houghton Mifflin, Boston.

Leisering, L. & Leibfried, S. (1999): Time and Poverty in Western Welfare States: United Germany in Perspective. Cambridge University Press.

Lewis, O. (1966): The culture of poverty. *Scientific American.* Vol.215, pp 19–25.

Lipset, S. M. & Bendix, R. (1959): Social mobility in industrial society. Heinemann, London.

Mack, J. & Lansley, S. (1985): Poor Britain. George Allen & Unwin, London.

Marks, C. (1991): The Urban Underclass. *Annual Review of Sociology* 17, pp. 445–466.

Marshall, T. H. (1975): Social Policy. Hutchinson, London.

McCall, J. J. (1971): A Markovian model of income dynamics. *Journal of the American Statistical Association* 66:335, pp. 439–447.

McCutcheon, A. L. (1987): Latent Class Analysis. Sage University Paper series on Quantitative Applications in the Social Sciences. Sage, Beverly Hills.

Messick, S. (1989): Validity *in* Educational measurement (ed. Linn, R. L.), American Council on Education and National Council on Measurement in Education. Washington D.C., pp. 13–103.

Moisio, P. (2002): The Nature of Social Exclusion – Spiral of Precariousness or Statistical Category? *in* Social Exclusion in European Welfare States (eds. Muffels, R. & Tsakloglou, P.), Edward Elgar, Cheltenham. pp. 170–183.

Moisio, P. (2004): A Latent Class Application to the Multidimensional Measurement of Poverty. *Quality & Quantity – International Journal of Methodology*. (forthcoming)

Moss, P. A. (1992): Shifting conceptions of validity in educational measurement: implications for performance assessment. *Review of Educational Research* 62:3, pp. 229–258.

Muffels, R., Berghman, J. & Dirven, H. (1992): A Multi-Method Approach to Monitor the Evaluation of Poverty. *Journal of European Social Policy* 2:3, pp. 193–213.

Nolan, B. & Whelan, C. T. (1996): Resources, Deprivation and Poverty. Clarendon Press, Oxford.

Nolan, B. & Whelan, C. T. (1999): Loading the Dice? A Study of Cumulative Disadvantage. Oak Tree Press, Dublin.

Nordberg, L. (2004): An analysis of the effects of using interview versus register data in income distribution analysis based on the Finnish ECHP-surveys in 1996 and 2000. CHINTEX Working papers. Federal Statistical Office Germany.

OECD (1998): Labour Force Statistics 1977–1997. OECD, Paris.

OECD (2001): OECD Social Expenditures Database 1980–1998. OECD, Paris.

Peracchi, F. (2002): The European Community Household Panel: A review. *Empirical Economics* 27, pp. 63–90.

Piachaud, D. (1987): Problems in the Definition and Measurement of Poverty. *Journal of Social Policy* 16:2, pp. 147–164.

Poverty in the United States: 2000 (2001). Current Population Reports. U.S. Census Bureau.

Pollak R. A. & Wales, T. J. (1979): Welfare Comparisons and Equivalence Scales. *The American Economic Review* 69:2, pp. 216–221.

Powers, D. A. & Xie, Y. (2000): Statistical Methods for Categorical Data Analysis. Academic Press.

Pöntinen, S. (1981): Models and social mobility research: a comparison of some log-linear models for a social mobility matrix. Department of Sociology, University of Helsinki.

Rendtel, U., Langeheine, R. & Berntsen, R. (1998): The estimation of poverty-dynamics using different household income measures. *Review of Income and Wealth* 44, pp. 81–98.

Rendtel, U., Nordberg, L., Jäntti, M., Hanisch, J. & Basic, E. (2004): Report on quality of income data. CHINTEX Working papers. Federal Statistical Office Germany.

Ringen, S. (1985): Toward a Third Stage in the Measurement of Poverty. *Acta Sociologica* 28:2, pp. 99–113.

Ringen, S. (1988), Direct and indirect measurement of poverty, *Journal of Social Policy*, 17: 3, pp. 351–65.

Ritakallio, V.-M. (2002): New Recommendations for Compilation of Statistics will Change the Cross-National Picture of Poverty in Europe. COST A15 meeting at Urbino, 25.10.2002.

Room, G. (ed.) (1995): Beyond the Threshold: The Measurement and Analysis of Social Exclusion. The Policy Press, Bristol.

Rowntree, B. S.(1941): Poverty and Progress: A Second Social Survey of York. Longmans, Green, London >> Rein, M. (1971): Problems in the Definition and Measurement of Poverty *in* The Concept of Poverty (ed. Townsend, P.) Heinemann Educational Books, Lontoo. p. 49.

Roy, A. D. (1951): Some Thoughts on the Distribution of Earnings. *Oxford Economic Papers* 3, pp. 135–146.

Ruggles, P. (1990): Drawing the line / Alternative poverty measures and their implications for public policy. Urban Institute Press, Washington.

Sahota, G. S. (1978): Theories of Personal Income Distribution: A Survey. *Journal of Economic Literature* Vol. XVI, pp. 1–55.

Sen, A. (1976): Poverty: An Ordinal Approach to Measurement. *Econometrica* 44:2, pp. 219–231.

Sen, A. (1977): On weights and measures. *Econometrica* 45, pp. 1539–72.

Sen, A. (1979): Issues in the Measurement of Poverty. *Scandinavian Journal of Economics* 81, pp. 285–307.

Sen, A. (1983): Poor, Relatively Speaking. *Oxford Economic Papers* 35, pp. 153–169.

Sen, A. (1985): A Sociological Approach to the Measurement of Poverty: A Reply to Professor Peter Townsend. *Oxford Economic Papers* 37, pp. 669–676.

Sen, A. (1992) Inequality reexamined. Oxford University Press.

Sen, A (2000): Social Exclusion: Concept, Application, and Scrutiny. Social Development Papers No. 1. Office of Environment and Social Development. Asian Development Bank.

Silver, H. (1994): Social Exclusion and Social Solidarity: Three Paradigms. *Int. Labour Review* 133:5–6, pp. 531–578.

Standards for educational and psychological testing. American Psychological Association. Washington, D.C. 1994.
Strobel, P. (1996): From Poverty to Exclusion: A Wage-Earning Society or a Society of Human Rights? ISSJ, vol. 148, pp. 173–189.
Sørensen, A. B. (2000) Towards a Sounder Basis for Class Analysis. *American Journal of Sociology* 105, pp. 1523–1558.
Titmuss, R. M. (1974): Social Policy. An Introduction. George Allen & Unwin, London.
Townsend, P. (1971): Measures and Explanation of Poverty in High Income and Low Income Countries: The Problems of Operationalizing the Concepts of Development, Class and Poverty *in* The Concept of Poverty (ed. Townsend, P.) Heinemann Educational Books, London, pp. 1–45.
Townsend, P. (1979): Poverty in United Kingdom. Penguin Books Ltd.. Middlesex.
Townsend, P. (1985): A Sociological Approach to the Measurement of Poverty - A Rejoinder to Professor Amartya Sen. *Oxford Economic Papers* 37, pp. 659–668.
Townsend, P. (1987): Deprivation. *Journal of Social Policy* 16:2, s. 125–146.
US Census Bureau (2004) <URL> www.census.gov/hhes/www/poverty.html
Van de Pol, F. & de Leeuw, J. (1986): A Latent Markov Model to Correct for Measurement Error. *Sociological Methods and Research* 15:1–2, pp. 118–141.
Van de Pol, F. & de Langeheine, R. (1990): Mixed Markov Latent Class Models. *Sociological Methodology* 20, pp. 213–247.
Vermunt, J. K. (1997): LEM: A general program for the analysis of categorical data – Manual. Tilburg University. <URL> http://www.kub.nl/faculteiten/fsw/organisatie/departementen/mto/software2.html
Walker, R. (1994): Poverty Dynamics: issues and examples. Aldershot. Avebury.
Watson, D. (2002): Sample Attrition between Waves 1 and 4 in the European Community Household Panel. Doc PAN 185/02. Eurostat, Luxembourg.
Watts, H. (1968): An Economic definition on Poverty *in* On Understanding Poverty (ed. Moynihan, D. P.), Basic Books, New York. pp. 316–329.
Whelan, C. T., Layte, R., Maître, B. & Nolan, B. (2000): Poverty Dynamics: an Analysis of the 1994 and 1995 Waves of the European Community Household Panel. *European Societies* 2:4, pp. 505–531.
Whelan, C. T., Layte, R., Maître, B. & Nolan, B. (2001): Income, Deprivation, and Economic Strain. An Analysis of the European Community Household Panel. *European Sociological Review* 17:4, pp. 357–72.
Whelan, C. T., Layte, R. & Maître, B. (2002): Persistent Deprivation in the European Union. *Journal of Applied Social Science Studies* 122, pp. 31–54.
Wiley, D. E. & Wiley, J. A. (1970): The Estimation of Measurement Error in Panel Data. *American Sociological Review* 35:1, pp. 112–117.
Wilson, J. (1987): The Truly Disadvantaged: The Inner City, the Underclass and Public Policy. University of Chicago Press, Chicago.
Wrong, D. H. (1959): The Functional Theory of Stratification: Some Neglected Considerations. *American Sociological Review* 24:5, pp. 772–82.
Wright, E. O. (1997) Class Counts. Comparative Studies in Class Analysis. Cambridge, Cambridge University Press.

LEM syntaxes for the log-linear models

Variables	**Description**
A, B, C and D:	Repeated classifications in waves 1,2,3 and 4.
M:	Poverty dynamics: income dynamics = 1, deprivation dynamics = 2, subjective dynamics = 3.
T:	Countries: Denmark = 1, Netherlands = 2, Belgium = 3, France = 4, Ireland = 5, Italy = 6, Greece = 7, Spain = 8, Portugal = 9, United Kingdom = 10.

Independence

```
man 4
dim 2 2 2 2
lab A B C D
mod {A,B,C,D}
```

Quasi-Independence

```
man 4
dim 2 2 2 2
lab A B C D
mod {A,B,C,D,fac(ABCD,2)}
des [ 1 0 0 0 0 0 0 0
      0 0 0 0 0 0 0 2 ]
```

Simple Markov

```
man 4
dim 2 2 2 2
lab A B C D
mod B|A
    C|B eq1 B|A
    D|C eq1 B|A
```

Simple Markov*

```
man 4
dim 2 2 2 2
lab A B C D
mod {AB,BC,CD}
```

Markov 2 Chain

```
lat 1
man 4
dim 2 2 2 2 2
lab X A B C D
mod B|AX
    C|BX eq1 B|AX
    D|CX eq1 B|AX
```

Mover-Stayer

```
lat 1
man 4
dim 2 2 2 2 2
lab X A B C D
mod A|X
    B|AX eq2
    C|BX eq1 B|AX
    D|CX eq1 C|BX
des [1 2 3 4 -1 -1 -1 -1]
sta B|AX [.5 .5 .5 .5 1 0 0 1]
```

Time-heterogen. Mover-Stayer

```
lat 1
man 4
dim 2 2 2 2 2
lab X A B C D
mod A|X
  B|XA eq2
  C|XB eq2
  D|XC eq2
des [0 0 0 0 -1 -1 -1 -1 0 0 0 0
-1 -1 -1 -1 0 0 0 0 -1 -1 -1 -1 ]
sta B|XA [.25 .25 .25 .25 1 0 0 1]
sta C|XB [.25 .25 .25 .25 1 0 0 1]
sta D|XC [.25 .25 .25 .25 1 0 0 1]
```

Latent Class

```
lat 1
man 4
dim 2 2 2 2 2
lab X A B C D
mod X
  A|X
  B|X eq1 A|X
  C|X eq1 A|X
  D|X eq1 A|X
```

Latent Class*

```
lat 1
man 4
dim 2 2 2 2 2
lab X A B C D
mod X
  A|X
  B|X
  C|X
  D|X
```

Appendix continues

Latent Markov	**Time-heterogen. Latent Markov**	**(Partially) Latent Mover-Stayer**
lat 4 man 4 dim 2 2 2 2 2 2 2 2 lab X Z Y W A B C D mod X A|X B|Z eq1 A|X C|Y eq1 A|X D|W eq1 A|X Z|X Y|Z eq1 Z|X W|Y eq1 Z|X	lat 4 man 4 dim 2 2 2 2 2 2 2 2 lab X Z Y W A B C D mod X A|X B|Z eq1 A|X C|Y eq1 A|X D|W eq1 A|X Z|X Y|Z W|Y	lat 5 man 4 dim 2 2 2 2 2 2 2 2 2 lab U V W X Y A B C D mod A|UV eq2 B|UW eq1 A|UV C|UX eq1 A|UV D|UY eq1 A|UV W|UV eq2 X|UW eq2 Y|UX eq2 des [0 0 0 0 -1 -1 -1 -1 0 0 0 0 -1 -1 -1 -1 0 0 0 0 -1 -1 -1 -1 0 0 0 0 -1 -1 -1 -1] sta A|UV [.25 .25 .25 .25 1 0 0 1] sta W|UV [.25 .25 .25 .25 1 0 0 1] sta X|UW [.25 .25 .25 .25 1 0 0 1] sta Y|UX [.25 .25 .25 .25 1 0 0 1]
Common Fluidity	**Latent Common Fluidity**	
man 5 dim 3 2 2 2 2 lab M A B C D mod {MA,MB,MC,MD,ABCD}	lat 4 man 5 dim 2 2 2 2 3 2 2 2 2 lab V W X Y M A B C D mod A|MV eq2 B|MW eq1 A|MV C|MX eq1 A|MV D|MY eq1 A|MV W|MV {WM, WV} X|MWV {XM, XWV} Y|MXWV {YM, YXWV} des [0 0 0 0 0 0 0 0 0 0 0 0] sta A|MV [.75 .25 .75 .25 .75 .25 .25 .75 .25 .75 .25 .75]	

Proportions of item nonresponce*

		Financial poverty		Housing deprivation		Subjective deprivation	
Country	N	NR in i	NR in 1	NR in i	NR in 1	NR in i	NR in 1
DK	5 448	19,2 %	2,6 %	7,9 %	1,0 %	7,4 %	1,1 %
NL	10 667	12,1 %	2,6 %	2,7 %	0,1 %	2,6 %	0,1 %
B	7 280	13,0 %	2,8 %	5,6 %	2,3 %	5,2 %	2,4 %
F	14 456	10,9 %	1,7 %	4,5 %	0,3 %	3,8 %	0,4 %
IRL	9 144	9,7 %	0,2 %	5,1 %	0,8 %	1,4 %	0,5 %
I	18 622	14,5 %	4,5 %	5,6 %	3,1 %	4,5 %	1,9 %
EL	12 372	13,6 %	1,1 %	0,7 %	0,0 %	0,8 %	0,0 %
E	16 709	16,4 %	2,6 %	4,5 %	0,2 %	4,1 %	0,1 %
P	12 686	8,9 %	1,8 %	2,4 %	0,0 %	2,5 %	0,0 %
UK	10 892	5,7 %	2,4 %	32,8 %	25,9 %	4,9 %	2,2 %

* N is the number of cases (unweighted), NR in *i* is the proportion of cases in the panel having at least one missing value, NR in 1 is the proportion of missing values in the first wave.