5. Wage Mobility for Low-Wage Earners in Denmark and Finland[1]

R. Asplund, P. Bingley and N. Westergård-Nielsen

1 INTRODUCTION

A number of studies of wage mobility have shown that the mobility of wage rates of wage earners is actually much larger than commonly thought (OECD 1996). Part of this mobility is found to be related to normal life-cycle mobility where individuals start at some point after having completed full-time education, and move upward until the end of their working career. Life-time inequality is thus created by someone dropping behind in the race for the 'normal' upward mobility. Another part is related to factors that individuals themselves (or policy makers) can influence, including attachment to the labour market, child care, type of work etc. Several results (e.g. Asplund et al. 1996) show that general human capital such as education and experience are important determinants of where people are observed in the wage distribution. Upward wage mobility, in turn, is found to be associated with higher education, less unemployment, less experience and the absence of changes in occupation and industry. Furthermore, high individual mobility is noted to be compatible with unchanged overall wage dispersion as measured by Gini coefficients.

This chapter investigates the year-to-year mobility of wages for two private-sector samples of low-wage earners in Denmark and Finland. Unlike previous work in this field we are estimating a model for the change in percentile rank in the wage distribution for each individual. Furthermore, we adjust for sample selection bias due to attrition and only looking at those persons who have ever been in the lowest quintile. One of the problems with previous estimations has been that they do not adjust for the fact that a substantial attrition happens from the lowest and highest wage deciles. The adopted model also attempts to control for unobserved heterogeneity among the observed persons. Furthermore, the model also distinguishes between different levels of mobility.

Especially for policies toward the low-wage earners it is important to identify factors that make it more likely that a person will drop behind in the race for lifetime upward mobility and thus become a low-wage earner. On the other hand it is also crucial to identify groups of individuals for whom low mobility is only a temporary phenomenon. These findings have consequences for policies concerning minimum wage setting and job creation schemes. The traditional political concern is related to a static perception of those at the low end of the wage distribution and neglects the fact that many actually move upward in the wage distribution if they get started on a work career.

The chapter deals with two countries, Denmark and Finland, and seeks to identify commonalities and differences in what makes people upwardly or downwardly mobile in these two countries. The study focuses exclusively on the upward and downward mobility for individuals who at some point in time have been in the lowest quintile of the wage distribution, i.e. among the lowest 20 per cent. In contrast to previous studies for Denmark and Finland (Bingley et al. 1995, Asplund and Bingley 1996) analysing wage mobility among (all) deciles of the wage distribution, here we quantify the degree of mobility and consider this relative to each individual's starting position in the wage distribution. Only movements exceeding a threshold of 1 per cent in either direction are considered as mobility. The main advantage of this approach is that we avoid problems of treating situations where people are very close to a quintile threshold equal to situations where they are far from the threshold.

Another point to mention is that in this study we are exclusively dealing with wage rates and not income or earnings. The main problem with the latter measures is that they also involve a labour supply decision which may be considered to be endogenous. However, many studies still use income or earnings because of shortcomings in data availability and the desire to implement standard estimation techniques for balanced panel data.

2 PREVIOUS STUDIES

A recent comprehensive survey of empirical studies of earnings mobility is found in Atkinson et al. (1992). (See the Introduction to this volume.) A selected number of studies of individual mobility are briefly discussed below to illustrate some of the different approaches that have been used.

2.1 Measures

As outlined in the Introduction to this volume, several methods of measuring mobility have been proposed. If focusing on a raw transition matrix, it is natural to count the proportion of immobile observations on or near the diagonal. Similarly one can count the periods the observed individuals stay below some threshold income of interest (part of the analyses of Gottschalk 1982, and Lillard and Willis 1978). Quantifying the size of individual transitions over longer time periods may be informative, and one can calculate the average absolute cell jump. Cells of the transition matrix have been variously defined: money earnings (Hart 1976), income relative to the mean (Thatcher 1971).

Inflation of nominal income means, however, that absolute transitions are observed also without any relative changes. The alternative is to look at the individuals' relative position in the distribution, whereby the relative position can be calculated using e.g. quintiles or deciles. Mobility is then measured as movements between one decile/quintile in time t to another decile/quintile in time $t+1$.

This method has the virtue of being in accordance with the tradition of income distribution studies. In particular, being an order statistic it is robust to outliers. This is important especially when considering hourly wages constructed from earnings over hours because hours are prone to measurement error. For policy purposes those at the bottom end of the wage distribution are of greatest interest, and it is obvious that outliers are grouped at the extremes of the distribution. Temporary and part-time workers, for instance, are commonly found among the low-wage earners, one reason being that measurement errors in hours are most likely to occur for these individuals. Obviously a large proportion of measurement error shows up also among those (outliers) transiting many deciles in a single period. The imprecisely calculated wage rate for many samples may therefore motivate broad grouping.

Measures of individuals' relative positions are, though, open to the criticism that income ranges are closer towards the middle of the distribution, meaning that even a small 'push' may be sufficient to contribute to the mobility. In fact, investigation of the distribution of transitions originating around the wage decile thresholds using Danish data points to some degree of grouping when focusing on movements out of a decile during a single year (Bingley et al. 1995). This effect is much less severe when analysing transitions over a longer period of time because the changes in decile are more stable in the longer run; the potential grouping problem seems almost to disappear when investigating a four-year period.

From a normative perspective it is interesting to link mobility and lifetime inequality. Mobility may be seen as the degree to which annual inequality differs from lifetime inequality, where lifetime inequality is calculated as the weighted (according to proportion of lifetime incomes) average of individual annual inequalities (e.g. Shorrocks 1978). The measurement of inequality literature (recently surveyed in Lambert 1993) puts forward a variety of single index summary measures, such as the Gini coefficient, Theil index, square of coefficient of variation, indices giving a coefficient conditional on a choice of parameter and partial orderings such as Lorenz curves. However, lifetime averages of these measures often fail to agree on unique rankings (as shown in Shorrocks 1981). Classes of dominance criteria analogous to the static inequality literature have yet to be developed in the context of income mobility (see Atkinson et al. 1992).

There are essentially two ways to proceed if one is interested in inequality indices over different time periods. First, for shorter panels estimate dynamic earnings equations and use these to simulate lifetime earnings trajectories (see Lillard 1977 for an example). Second, use longer panels which can be approximated for example to the working lifetime (a good recent example is Björklund 1993) to calculate annual and longer-run inequality indices. Clearly, the former is more liable to measurement error and mean-reverting bias associated with being unable to predict well from individual-specific unobservables.

The majority of the literature uses measures of mobility which result from various stochastic specifications of changes in incomes or wages over time. McCall (1971) estimates a first-order Markov model for poverty transitions. Hart (1976) considers a simple Galton–Markov model of regression towards the mean. Schiller (1977) describes a ventile transition matrix. Shorrocks (1978) proposes a mobility index for transition matrices based on the convergence speed of a Markov chain. MaCurdy (1982) estimates a complex autoregressive moving average structure by quasi-maximum likelihood. These are all purely statistical models.

2.2 Models

A rich representation of earnings dynamics is obtained in models where the main focus is on earnings determinants. This specification allows for a distinction between permanent and transitory sources of mobility.

$$\log W_{it} = X_i\alpha + Y_{it}\beta + \upsilon_{it} \tag{5.1}$$

$$\upsilon_{it} = \lambda_i + \mathrm{v}_i(t - \bar{t}) + \varepsilon_{it} \tag{5.2}$$

The logarithm of the real wage W_{it} of individual i in period t is assumed to be determined by permanent observed characteristics, X_i and Y_{it}. Unobserved individual attributes are captured by individual-specific terms in υ_{it}. The individual effect λ_{it} represents unmeasured characteristics like productivity that affect the level of earnings persistently and v_{it} represents unmeasured variables like learning ability which influence earnings growth. The variance term ε_{it} gives a measure of the true transitory component of earnings.

Lillard and Weiss (1979) is a study using this formulation with an added serial correlation in the error term. Berry et al. (1988) use PSID data for 1975–81 to examine the effect of plant closure on US earnings. It is found that mean earnings decrease and variance increases, but this effect diminishes over time since displacement. Gottschalk (1982) uses NLS data for 1966–75 to consider the above model but omits serial correlation and individual explanatory variables. This enables a minimal decomposition into permanent and transitory earnings. A poverty threshold is imposed and the number of periods individuals are below it is counted from actual observed and predicted permanent earnings. An ordered logit (using demographic controls) is estimated on the number of periods of non-transitory poverty. It is found that 43 per cent of individuals with low earnings in a random year had low earnings in all years of the study. This implies a great deal of permanency among the poor.

2.3 Attrition

Attrition bias may understate mobility as a result of focusing on those stable individuals staying within the sample. Keane et al. (1988) studied the movement of real wages over the business cycle using NLS-YM data for 1966–81. They found that failure to account for self-selection biased real wages procyclically. This is attributed to workers with a low permanent wage (associated with low education and high incidence of unemployment) as well as those with high transitory wages being more likely to lose employment in a recession.

Stewart and Swaffield in Chapter 7 of this volume, estimate poverty transitions on British data (BHPS). The focus of their study is on controlling for the potential endogeneity of sample attrition and the origins of the mobility process. This is, in fact, the only other study we are aware of that attempts to account for such issues which may otherwise seriously call into question the statistical generality of wage mobility estimation. Though unobserved individual heterogeneity is not controlled for in the Stewart–Swaffield study, it is something we do allow for and which we find to be important.

3 THE ECONOMETRIC FRAMEWORK

3.1 Chosen Measure of Mobility

In this study wage mobility is measured as the year-to-year change in the individual's percentile rank in the wage distribution. The idea thus is to rank all observations according to their hourly wage rate and subsequently measure the percentage change in rank between two points in time, in this case for a group of low-wage earners defined as those individuals who have ever been in the lowest quintile. This wage mobility measure has the benefit of combining the advantages of a relative measure with the fact that we avoid problems linked to the use of wage thresholds.

3.2 Selectivity Bias

Any attempt to identify determinants of individual mobility within the wage distribution over time will face two potential sources of selectivity bias. First, the results may be influenced by a potential sample selection bias due to panel attrition, i.e. to mobility being observed only for those who have a positive wage both in the starting and the destination year. Even in the best panel data sets, a certain number of individuals will leave the sample due to natural causes, unemployment or retirement. Alternatively they may become self-employed. These individuals falling outside the estimation sample may be of interest in their own right, e.g. in representing people with a weak attachment to the labour market. Hence, focusing merely on individuals having a positive wage in both periods, thus ignoring these exits, might seriously bias the results by understating both upward and downward wage mobility. This problem is important in the present study because we are in both countries relying on establishment-level data where people are most often observed within the same establishment or industry.

Second, ignoring the fact that the individuals' starting positions in the wage distribution depend on their background characteristics may lead to possible endogeneity bias. As mentioned earlier individuals might be observed in the lower end of the wage distribution at a given point in time due to a clearly transitory variation in their wages. For example, a young person with a high education may have temporarily accepted a low-wage job, although he would undoubtedly have been higher up in the wage distribution had he started in a 'normal' job. Most likely he will, therefore, quickly move upwards in the wage distribution. In contrast to most previous studies of individual wage mobility, the present study covers both types of selectivity.

3.3 Unobserved Heterogeneity

Unobserved heterogeneity is supposed to influence both mobility and attrition in different ways. First, it can be assumed that the individual will over time be hit by certain shocks from the surrounding economy or from the person himself. These might be job changes or changes in the local labour market or changes in family relations or some other factor that affects the productivity of the individual. Second, each individual will have some characteristics that are constant over time and that will influence the risk of leaving the sample or of being mobile. One example could be special skills or high ability. Such unobservables are in the present study accounted for in an error components framework as permanent heterogeneity as opposed to transitory noise.

3.4 The Econometric Model

The approach followed here is motivated primarily by concern for labour market policies. As a consequence, the gross hourly wage rate is the income concept of interest. The population of greatest relevance has a weak attachment to the labour market and is made integral to the adopted approach by estimating a limited error covariance matrix and simultaneously allowing for non-random attrition. The approach used is reduced form. In particular, using information on the individuals' background characteristics, the probability of moving from one quintile to another within the wage distribution is estimated simultaneously with the probabilities of having a positive wage both in the starting and the destination year and of belonging to a specific origin quintile. In other words, controls are imposed for potential sample selection bias as well as for potential endogeneity bias.

For all those who do not disappear from the sample in a given year we can observe wage mobility as a change in percentile rank. This is computed from the year-on-year difference in normalized ranks and divided into 41 categories. As a consequence we are estimating three simultaneous equations: a mobility equation that describes the changes in rank: an attrition equation that describes the probability that someone's wage is not observed in a period and an origin equation that determines the initial conditions of the mobility process. Further details of the econometric model can be found in the Appendix.

4 DATA

The Danish data are a representative 5 per cent sample of private-sector workplaces taken from Statistics Denmark administrative records. The time period covered is 1980–91. A worker is followed so long as (s)he is employed in a sampled workplace and one year before and after this attachment. The Finnish data originates from the Confederation of Finnish Industry and Employers (TT) records. This is a sample of every 15th worker employed in a member firm of the Confederation extending from 1980 to 1994. A worker is followed so long as (s)he is employed at an establishment of a member firm.

Danish private-sector workers are relatively mobile and consequently attrition is high in Denmark when using this data set. The observed attrition is clearly smaller in the Finnish data, which might be due to the fact that the member firms of the Confederation cover about 75 per cent of all workplaces within manufacturing and only a minor part of the more mobile service sector. The following description gives some idea about overall wage mobility.

Table 5.1 Mobility out of the lowest quintile (pooled data, percentage)

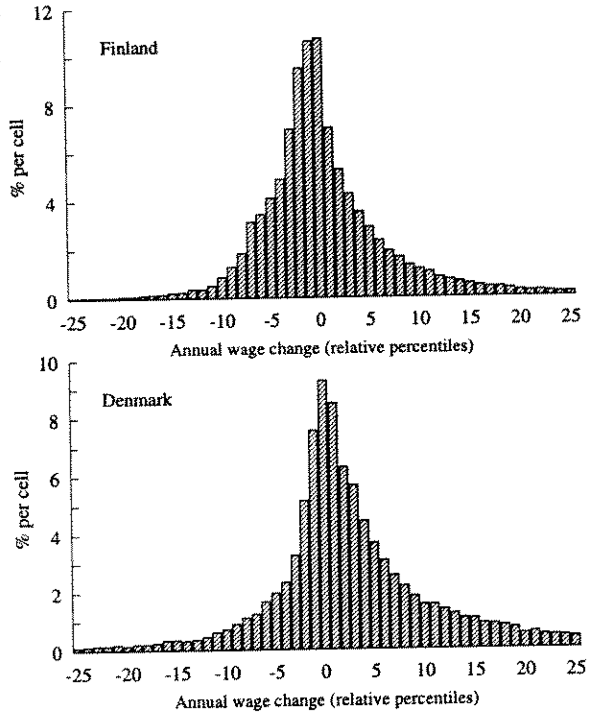
Denmark 1981–91							
Number of persons ever seen		1st	2nd	3rd	4th	5th	Sum
in the first quintile	54 085	65	22	7	4	2	100
in the second	42 632	0	55	30	12	3	100
in the third	32 265	0	0	57	34	9	100
in the fourth	25 986	0	0	0	66	34	100
in the fifth	20 663	0	0	0	0	100	100
Total	175 631	20	20	20	20	20	100
Finland 1980–94							
Number of persons ever seen		1st	2nd	3rd	4th	5th	Sum
in the first quintile	100 117	62	28	7	2	1	100
in the second	71 652	0	47	41	11	2	100
in the third	52 407	0	0	49	45	6	100
in the fourth	43 696	0	0	0	65	35	100
in the fifth	41 607	0	0	0	0	100	100
Total	309 479	20	20	20	20	20	100

First of all we have organized all individual hourly wage rates into quintiles. Table 5.1 shows, with the data pooled for all years investigated, how large a share of those who have ever been observed in the lowest quintile will also turn up in a higher quintile. Among the 54 085 observations of individuals in Denmark who have ever been in the lowest quintile, 65 per cent have persistently stayed in the 1st quintile, while 22 per cent have at some point in time also been in the 2nd quintile. Only 13 per cent have turned up in the 3rd or a higher quintile. This means that 35 per cent of all individuals who have ever been in the lowest quintile are also found in higher quintiles. The corresponding figure for Finland is 38 per cent.

The table further shows that in Denmark 45 per cent of those individuals who have had their lowest appearance in the 2nd quintile are actually also found in higher quintiles. For Finland this share is even higher at 53 per cent. The general tentative conclusion to be drawn is that the first quintile is more difficult to leave than the 2nd quintile. The final outcome, however, depends completely on how attrition is distributed across individuals.

Figure 5.1 reports the distribution of changes in individual percentile ranks between two consecutive periods. For both countries the distribution has a mean value around zero. While the distribution for Denmark is skewed

Figure 5.1 Wage mobility distribution



to the right with a positive median value to the right of zero, the distribution for Finland is more skewed to the left and has a negative median indicating that people in the Finnish sample are more likely to move downwards than upwards if they remain employed, all else equal. The explanation is that people in Finland tend to disappear from the bottom of the wage distribution, while attrition in Denmark to a larger extent happens from the upper end of the distribution.

The subsequent analysis will focus exclusively on the mobility for those who have ever been in the lowest quintile. Although there are a number of people who start out in higher quintiles before they 'visit' the lowest one, most individuals in the lowest quintile also start out here. Table 5.2 shows that in Denmark only some 10 per cent of all individuals ever observed in the lowest quintile start out higher up in the wage distribution, compared to 16 per cent in Finland (upper panel of Table 5.2). In order to simplify our model,

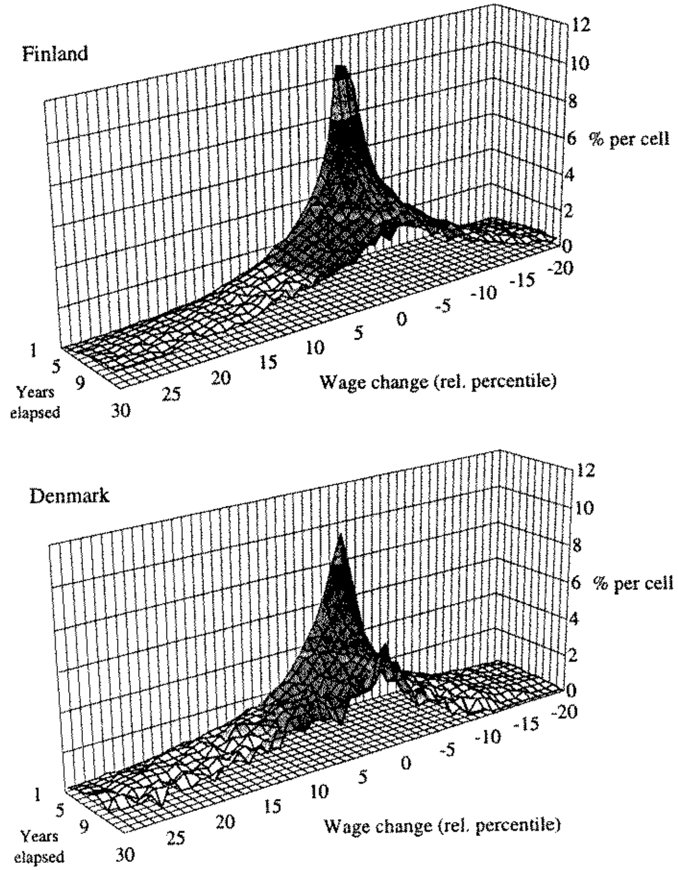
Table 5.2 Number of periods before and after being observed in the lowest quintile

Number of periods before first observed in lowest quintile	DENMARK			FINLAND		
	Frequency	Per cent	Cum. share	Frequency	Per cent	Cum. share
-14	–	–	–	39	0.04	0.04
-13	–	–	–	72	0.07	0.11
-12	–	–	–	127	0.13	0.24
-11	–	–	–	212	0.21	0.45
-10	20	0.04	0.04	320	0.32	0.77
-9	42	0.08	0.11	428	0.43	1.20
-8	76	0.14	0.26	542	0.54	1.74
-7	128	0.24	0.49	661	0.66	2.40
-6	194	0.36	0.85	793	0.79	3.19
-5	289	0.53	1.38	971	0.97	4.16
-4	439	0.81	2.20	1 203	1.20	5.36
-3	691	1.28	3.47	1 557	1.56	6.92
-2	1 098	2.03	5.50	2 280	2.28	9.19
-1	2 552	4.72	10.22	6 788	6.78	15.97
Number of periods after observed in lowest quintile						
1	8 957	16.56	61.41	15 908	15.89	50.66
2	5 933	10.97	72.38	10 728	10.72	61.38
3	4 185	7.74	80.11	8 175	8.17	69.54
4	3 093	5.72	85.83	6 553	6.55	76.09
5	2 323	4.30	90.13	5 229	5.22	81.31
6	1 761	3.26	93.38	4 309	4.30	85.62
7	1 339	2.48	95.86	3 520	3.52	89.13
8	1 019	1.88	97.74	2 858	2.85	91.99
9	753	1.39	99.14	2 316	2.31	94.30
10	467	0.86	100.00	1 868	1.87	96.17
11	–	–	–	1 432	1.43	97.60
12	–	–	–	1 090	1.09	98.68
13	–	–	–	791	0.79	99.47
14	–	–	–	526	0.53	100.00
Total	54 085	100	–	100 117	100	–

we have excluded these observations from the analysis. We are, in other words, only looking at those who are either staying within the 1st quintile or moving up (lower panel of Table 5.2).

Another dimension of the mobility measure is the time horizon over which it is measured, which allows us to explore how the short-run mobility depicted in Figure 5.1 is related to long-run mobility. Figure 5.2 repeats the exercise that was performed (from one year to the next) in Figure 5.1, for

Figure 5.2 Wage mobility distribution over time among those who are for the first time observed in the lowest quintile



longer time intervals. The original figure is now at the back wall of the box, and as more years elapse between comparisons we move towards the front of the box. The result is that the distributions spread out. It is, however, remarkable that the mean remains of the same sign throughout, so the downward trend in overall mobility for Finland is maintained. Sampling variance increases as we consider years further apart (especially for Denmark) because of attrition from the sample plus the fewer combinations of available years as the number of years elapsed increase.

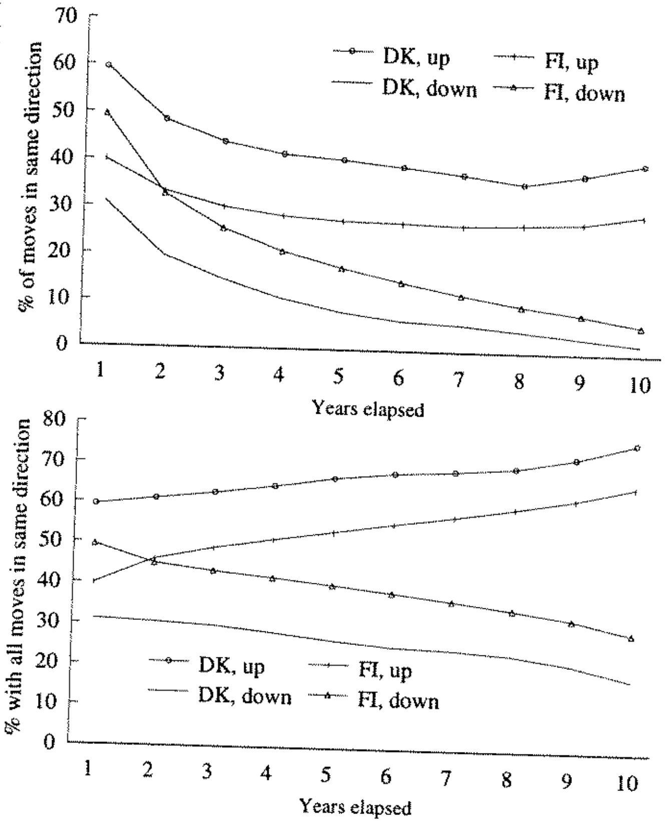
However, even these mobility distributions conceal churning in the wage distribution. In Figure 5.2 we are merely considering the end point of a process, and neglecting individual histories which may have been up and down along the way. We attempt to capture aspects of this in Figure 5.3. The upper part shows mobility trends. An individual could be said to have a mobility trend if, over a given time period, most moves were in the same direction. With random movement and the absence of any individual trends on average of those mobile, one-half of all moves would be in each direction. The immobile are not graphed, which explains why the sum of up and down moves is reduced to less than 100 per cent by the proportion of non-moves.

In Denmark upward mobility is from the outset more common than downward mobility, and this proves to be a trend with later moves in the same direction outnumbering the rest. For Finland, downward mobility is initially slightly more important. As the time horizon lengthens the proportion of moves up increases, and the proportion of moves down falls. Abstracting from business cycle effects as one does over the long period, simple life-cycle upward mobility remains, as is to be expected. Part of the reason is that we are increasingly neglecting all those persons who drop out of the sample. The graphs in Figure 5.3 nevertheless lead us to conclude that long-run trends are not necessarily apparent in the short run and indeed the evidence may be contradictory, as in the case of Finland. Short-run mobility measures may, as a result, be misleading.

The lower part of Figure 5.3 shows the persistence of individual wage mobility over time, i.e. the number of subsequent moves in the same direction as the time horizon lengthens. Random movement would give exponential decay in persistence. However, we observe that persistence declines much more slowly, obviously starting at the same point in time as in the upper part. As the time frame expands a lower proportion moves constantly in the same direction, but the reduction in this proportion falls as we consider longer periods. This suggests the existence of a group of persistent one-direction movers, which points to individual heterogeneity rather than state dependence.

These findings give an idea of the stability of progression of individuals through the wage distribution. After the first year the positive difference

Figure 5.3 *Trends (upper graph) and persistence (lower graph) in long-run wage mobility among those who are for the first time observed in the lowest quintile*



between persistent upward and persistent downward movers increases (up to a limit). Between 50 and 60 per cent of all low-wage earners have after 10 years experienced both moves up and down the wage distribution. For Denmark the long-run rate of persistent upward mobility is about 40 per cent, while it is about 30 per cent for Finland. These are individuals who always move up the wage distribution. The long-run downward persistence rate is lower: less than 8 per cent in Finland and even lower in Denmark. It is, however, not obvious that the process has stabilized after 10 years in Finland due to the unprecedented recession.

All of these effects are based on the hourly wage rates of the sample persons. This means that our findings may be biased by the fact that the attrition is not randomly distributed and that we are probably more likely to see people leave the sample from the lower end of the wage distribution than from the upper. In order to deal with this problem, we propose a statistical model that corrects for these factors and which can produce corrected estimates of mobility and its determinants.

5 ESTIMATIONS

Direct interpretation of the estimated parameters in an ordered model is not straightforward because marginal changes come through the different parts of the model as well as indirectly. Full estimates are nevertheless presented in Tables 5.A1 and 5.A2 in the Appendix to give an idea of sign, relative magnitude and significance.

Three equations are estimated jointly. The *origin quintile* equation can be thought of as a simple cross-section level of earnings function, except that the wage rate is split into ordered groups. Thus, a positive sign indicates a higher initial wage or higher starting quintile. The *attrition* equation is simply a binomial panel probit, and a positive sign indicates higher probability of leaving the sample. The *mobility* equation is of primary interest and is similar to a wage equation in first differences. Here, however, the percentile rank differences are split into groups, and all we may directly infer from a positive sign is that upward mobility is more likely than downward mobility. Simultaneity of origin and non-attrition are controlled for, and the mobility coefficients are consequently unbiased.

Consider first the origin equation. The estimates are entirely conventional for both countries regarding returns to human capital: quadratic age profile, positive return to longer education. Furthermore, there is a traditional occupational hierarchy and a large premium for men.

The attrition equation is an auxiliary catch-all function, since we do not specify out of sample destination. Accordingly, attrition captures a mix of transitions into retirement, study, self-employment, emigration, jobs outside the sampled firms and long-term unemployment. Theoretical priors regarding the net effects of explanatory variables are weak here. The coefficients are, however, remarkably similar for the two countries. Those with higher education, men and the young and the old are most likely to leave the sample (minimum attrition level obtained for the 40-year-olds in Finland and for the 45-year-olds in Denmark). The first three findings are due mainly to re-employment elsewhere, the latter to retirement and unemployment. Non-manual workers are the least likely to leave the sample in both countries.

The mobility function shows that low-wage males in both countries are more downwardly mobile than low-wage women. Mobility in Denmark is found to be negative quadratic in experience, measured as actual rather than the usual potential, as should be expected from the slope of a wage trajectory–experience profile. The maximum is found for 7.4 years. For Finland mobility is found to be more and more downward the longer experience, though the coefficient is rather small. Changes in occupation or skill group lead to upward mobility in both countries (though the effect is much larger in Finland) as these shifts are dominated by moves up the traditional occupational hierarchy. There is a wage mobility premium to geographical mobility in Finland, but not in Denmark. More education seems in Denmark to increase upward mobility, while this effect is weaker in Finland. Finance followed by manufacturing are the most upwardly mobile industries in Denmark. In Finland employees in the wood industry are most upwardly and construction workers most downwardly mobile. Wage mobility according to occupation in Denmark accords with the wage-levels skill hierarchy. In Finland, in contrast, non-manual workers are most upwardly mobile, but of these, technicians rather than managers are most upward mobile. Time controls show up very little for Denmark, but there is strong cyclicality for Finland, where upward mobility of low-wage earners is most important in economic upswings.

Table 5.3 reports the relationship between mobility and attrition which can be used to characterize the type of mobility in each industry. If mobility is accompanied by low attrition, it can be taken as an indication of improving work conditions, whereas downward mobility accompanied by high attrition indicates that people try to leave the industry because it is a declining sector. It can be seen that the high mobility is accompanied by relatively low attrition in metal, wood and paper for manual workers in Finland, whereas construction has downward mobility accompanied by higher attrition. The same pattern emerges for construction, trade and transport in Denmark. Only finance in Denmark shows upward mobility and low attrition. It is also remarkable, that manual workers in both countries seem to have lower mobility and more attrition. The same is also found for higher-level salaried employees.

Estimated variance and correlation terms are presented at the bottom of the two Appendix tables. All correlations, except one, are strongly significant, which indicates that endogeneity of origin and selectivity of non-attrition are important. Not taking this into account may bias the estimates of wage mobility.

Table 5.3 *Summary of estimation results for the lowest quintile*

Industry sector:	Finland				Denmark	
	Manual workers		Non-manual workers		All employees	
	Mobility	Attrition	Mobility	Attrition	Mobility	Attrition
Metal industry	0.14	-0.75	ref.	ref.	ref.	ref.
Wood industry	0.20	-0.72	0.07	0.15	-	-
Paper industry	0.34	-0.94	-0.01	-0.11	-	-
Construction	-0.08	0.00	-	-	-0.13	0.00
Other manufacturing	0.00	-0.11	-	-	-	-
Service sector	0.00	0.00	-	-	0.00	0.00
Trade	-	-	-	-	-0.15	0.07
Transport	-	-	-	-	-0.10	0.11
Finance	-	-	-	-	0.05	-0.13
Skill level:						
Skilled workers	-	-	-	-	0.11	0.06
Manual workers	0.00	0.58	-	-	-0.17	0.18
Clerical workers	0.06	-0.07	-	-	ref.	ref.
Upper non-manual	-0.06	0.00	-	-	-0.33	0.12

Notes: ref. refers to reference group in the estimations, and 0 indicates that the estimate is statistically insignificant.

Source: Tables 5.A1 and 5.A2.

Correlation between unobservables associated with mobility and those associated with attrition are of different sign for different components. In an error components framework, the individual effect can be thought of as a permanent effect related to individual unobservables, and the remainder error is simply a transitory component. Correlation between permanent unobservables is different to that between transitory unobservables. The permanent correlation $\rho_{\eta AM}$ is positive indicating that in the long run, those unobservable characteristics that make you more likely to leave the sample also make you more upwardly mobile. In the short run the opposite is the case in Finland, as shown by a negative $\rho_{\varepsilon AM}$, while the short-run effect is positive but insignificant in Denmark.

The net correlation (a sum of the two weighted according to group size), which would be estimated if the appropriate panel estimator was not implemented, is of indeterminate sign, and so sample selection may not be evident from pooled cross-sections of data. Unobservables associated with higher origin ($\rho_{\eta OM}$) are positively correlated with upward mobility in both countries. In the case of people with lower wages this correlation appears to be about the same size in the two countries. This suggests the same attrition processes in the two data sets. But this need not be the case and is purely an empirical question.

6 DIAGNOSTICS AND SIMULATIONS

Mis-specification tests in models such as these are frought with difficulties. As a crude diagnostic check we eyeball the predictions to see how well they fit the data. Goodness-of-fit measures for the primary equation of interest, mobility, are presented in Figure 5.A1 in the Appendix. The profiles of the observed distribution histograms are immediately apparent. The expected per cent in each category is calculated from summing (across individuals) the predicted probabilities of being in each state. Exactly on top of these is the predictive distribution. So we fit the curve perfectly, but nevertheless may be misclassifying everyone thereunder. The proportion expected to be in the correct cell is just the predicted probabilities multiplied by the observed and then summed over individuals. The extent to which our model fits better than random assignment (weighted by the right proportions in the right cell) is given by the height by which this line lies above the observed. The standard deviation of these predictions is relatively unimportant until 5 and 3 cells out, respectively. It is apparent from studying the distributions that the predictions are doing worse for downward mobility than for upward.

Is this a good or a bad fit? We may conclude that the model is not grossly misrepresenting the data. Recall that we are addressing an awkward question of relative wage movements, and not levels. This is notoriously difficult; data are fitted among 41 cells, jointly with the attrition and origin dimensions.

7 CONCLUSIONS

In this chapter we have investigated the year-to-year wage mobility for low-wage Danish and Finnish workers using comparable data for the private sector in the two countries. A model is estimated that takes into account that persons not observed for two consecutive years may differ non-randomly from others, and taking also into account that it may not be random from which quintile each person originates. It has been proven that neglecting the selection issue arising from only including the persons who can be observed in two consecutive years introduces bias into the estimates.

Estimates of the mobility functions show large similarities between the two countries. The results indicate that men in the group of low-wage earners in both countries are relatively more downwardly mobile than low-wage women. It seems as if higher experience in itself is related to downward mobility. In Finland this tendency can, however, be offset by acquiring more occupation-specific skills or by moving to another region. In Denmark, changing region is not associated with upward mobility, while human capital tends to be more positively related to mobility and higher experience leads to upward mobility over the first seven years of a labour market career.

NOTES

1 Comments from the participants at the LoWER conference held in Bordeaux 31 January and 1 February are gratefully acknowledged. Financial support from *Danmarks Grundforskningsfond*.

REFERENCES

Asplund, R., E. Barth, C. le Grand, A. Mastekaasa and N. Westergård-Nielsen (1996), 'Wage Distribution Across Individuals', in E. Wadensjö (ed.), *The Nordic Labour Markets in the 1990's*, vol. I, part 2, Amsterdam: North-Holland.

Asplund, R. and P. Bingley (1996), *Wage Mobility in Finnish Industry in 1980–1994*, Helsinki: ETLA The Research Institute of the Finnish Economy, Series B 123.

Atkinson, A.B., F. Bourguignon and C. Morrisson (1992), *Empirical Studies in Earnings Mobility*, London: Harwood.

Berry, S., P. Gottschalk and D. Wissoker (1988), 'An Error Components Model of the Effect of Plant Closing on Earnings', *Review of Economics and Statistics*, **70**, pp. 701–7.

Bingley, P., N.H. Bjørn and N. Westergård-Nielsen (1995), *Wage Mobility in Denmark 1980–90*, CLS Working Paper 95–10.

Björklund, A. (1993), 'A Comparison between Actual Distributions of Annual and Lifetime Income: Sweden 1951–89', *Review of Income and Wealth*, **39**(4), pp. 377–86.

Gottschalk, P. (1982), 'Earnings Mobility: Permanent Change or Transitory Fluctuations?', *Review of Economics and Statistics*, **64**(3), pp. 450–56.

Hart, P.E. (1976), 'The dynamics of earnings, 1963–1973', *Economic Journal*, **86**, pp. 551–65.

Keane, M., R. Moffitt and D. Runkle (1988), 'Real Wages over the Business Cycle: Estimating the Impact of Heterogeneity with Micro Data', *Journal of Political Economy*, **96**(6), pp. 1232–65.

Lambert, P. (1993), *The Distribution and Redistribution of Income*, Manchester University Press.

Lillard, L. (1977), 'Inequality: Earnings vs. Human Wealth', *American Economic Review*, **67**, pp. 42–53.

Lillard, L. and R.J. Willis (1978), 'Dynamic Aspects of Earnings Mobility', *Econometrica*, **46**(5), pp. 985–1012.

Lillard, L. and Y. Weiss (1979), 'Components of variation in panel earnings data: American scientists 1960–1970', *Econometrica*, **47**(2), pp. 437–54.

McCall, J.J. (1971), 'A Markovian model of income dynamics', *Journal of the American Statistical Association*, **66**, pp. 439–77.

MaCurdy, T.H. (1982), 'The Use of Time Series Processes to Model the Error Structure of Earnings in a Longitudinal Data Analysis', *Journal of Econometrics*, **18**(1), pp. 83–114.

OECD (1996), *Employment Outlook*, Paris.

Schiller, B. (1977), 'Relative earnings mobility in the US', *American Economic Review*, pp. 926–41.

Shorrocks, A.F. (1978), 'Income inequality and income mobility', *Econometrica*, **48**, pp. 613–25.

Shorrocks, A.F. (1981), 'The Measurement of Mobility', *Econometrica*, **46**(5), pp. 1013–24.

Thatcher, A.R. (1971), 'Year-to-year variations in the earnings of individuals', *Journal of the Royal Statistical Society*, Series A, **131**, pp. 374–82.

APPENDIX

Figure 5.A1 Goodness of fit

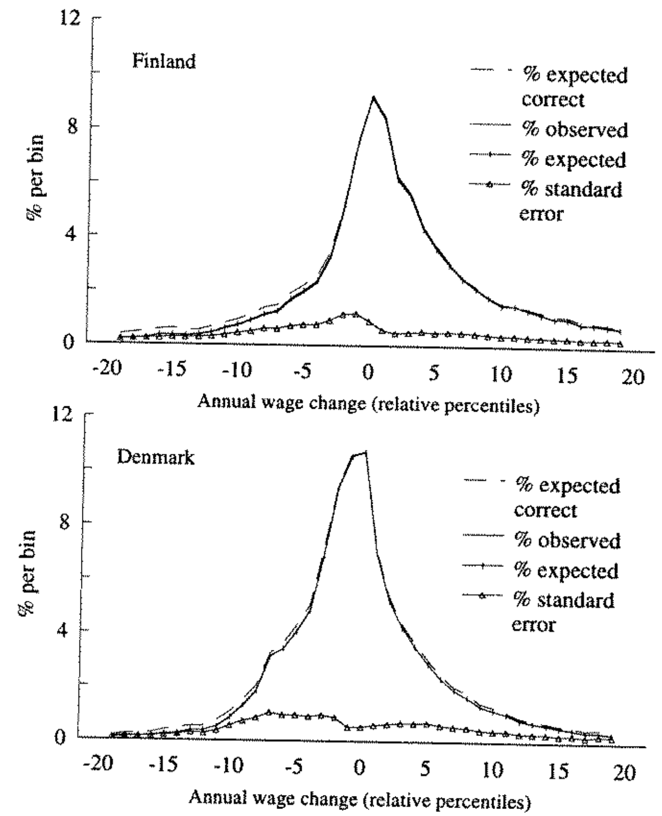


Table 5.A1 *Danish panel wage mobility 1981–91: model estimates (standard errors in parentheses)*

Variable	Equation					
	[EQN 'up'] Mobility		Attrition		Origin Quintile	
	Value	S. E.	Value	S. E.	Value	S. E.
Male	-0.0613	(0.0153)	0.0114	(0.0150)	0.7979	(0.0062)
Age/100	-		-10.1776	(0.3534)	1.7709	(0.0158)
Age2/1000	-		1.1219	(0.0462)	-0.2014	(0.0020)
Experience/10	0.0422	(0.0296)	-		-	
Experience2/1000	-0.2681	(0.0708)	-		-	
Δ Skill	0.0531	(0.0239)	-		-	
Δ Region	-0.0897	(0.0984)	-		-	
General	0.1565	(0.0251)	-0.2208	(0.0202)	-0.2056	(0.0109)
Vocational	0.1831	(0.0261)	-0.2516	(0.0211)	-0.0135	(0.0108)
College	0.2462	(0.0426)	-0.2643	(0.0432)	0.2887	(0.0161)
University	0.0250	(0.0493)	0.0741	(0.0461)	0.4699	(0.0153)
Construction	-0.1339	(0.0360)	0.0181	(0.0348)	0.1576	(0.0105)
Trade	-0.1492	(0.0168)	0.0670	(0.0171)	-0.3430	(0.0068)
Transport	-0.1032	(0.0363)	0.1055	(0.0365)	-0.3430	(0.0068)
Finance	0.0520	(0.0224)	-0.1285	(0.0235)	0.1634	(0.0091)
Services	-0.0329	(0.0208)	-0.0074	(0.0221)	-0.0659	(0.0090)
Manager	-0.3314	(0.0479)	0.1205	(0.0482)	0.9168	(0.0111)
Skilled	0.1055	(0.0254)	0.0631	(0.0243)	0.1468	(0.0083)
Unskilled	-0.1722	(0.0178)	0.1842	(0.0175)	-0.0472	(0.0078)
Other skill	-0.1945	(0.0205)	0.1720	(0.0190)	-0.1954	(0.0111)
København	-0.0017	(0.0238)	0.0879	(0.0246)	-	
Frederiksborg	0.0015	(0.0287)	0.0208	(0.0302)	-	
W. Sjöland	-0.0604	(0.0273)	-0.0027	(0.0293)	-	
S. Jylland	0.0000	(0.0274)	-0.0504	(0.0294)	-	
E. Jylland	-0.0145	(0.0249)	0.0145	(0.0263)	-	
W. Jylland	0.0111	(0.0282)	-0.0689	(0.0302)	-	
N. Jylland	-0.1012	(0.0290)	-0.0263	(0.0307)	-	
1981	0.8353	(0.0620)	-1.1423	(0.0295)	-	
1982	0.7755	(0.0615)	-1.1426	(0.0275)	-	
1983	0.7861	(0.0640)	-1.2215	(0.0271)	-	
1984	0.8556	(0.0602)	-1.1026	(0.0254)	-	
1986	0.7239	(0.0575)	-1.0180	(0.0239)	-	
1987	0.7070	(0.0582)	-1.0279	(0.0237)	-	
1988	0.7455	(0.0597)	-1.0723	(0.0236)	-	
1989	0.7849	(0.0593)	-1.0577	(0.0230)	-	
1990	0.7836	(0.0558)	-0.9486	(0.0224)	-	
(Year-81)/10	-		-		-0.0992	(0.0719)
(Year-81)2/100	-		-		0.0905	(0.1694)
(Year-81)3/1000	-		-		0.0065	(0.1101)
$\rho_{\varepsilon AM}$	0.1238 (0.0815)				-	
$\rho_{\eta AM}$	0.2499 (0.0678)				-	
$\rho_{\eta OM}, \rho_{\eta OA}$	0.3383	(0.0088)	0.0935	(0.0090)	-	
$\sigma_{\eta A}, \sigma_{\eta M}$	0.6083	(0.0189)	0.0334	(0.0342)	-	
Observations	29 762					
Log likelihood	-		-380 176		-	

Table 5.A2 *Finnish panel wage mobility 1980–94: model estimates (standard errors in parentheses)*

Variable	Equation					
	[EQN 'up'] Mobility		Attrition		Origin Quintile	
	Value	S. E.	Value	S. E.	Value	S. E.
Male	-0.0854	(0.0110)	0.0242	(0.0135)	1.1656	(0.0055)
Age/100	-		-11.8923	(0.3009)	1.6035	(0.0143)
Age2/1000	-		1.5170	(0.0392)	-0.1707	(0.0018)
Experience/10	-0.0769	(0.0237)	-		-	
Experience2/1000	0.0502	(0.0547)	-		-	
Δ Skill	0.5853	(0.0494)	-		-	
Δ Region	0.2608	(0.0308)	-		-	
Basic	0.0634	(0.0122)	-0.0634	(0.0150)	-0.6069	(0.0057)
Low secondary	0.0813	(0.0122)	-0.0634	(0.0150)	-0.6069	(0.0057)
College	0.0726	(0.0124)	-0.0924	(0.0150)	-0.4522	(0.0052)
Clothing	0.1196	(0.0589)	-0.0289	(0.0702)	0.5057	(0.0107)
Metal manual	0.1381	(0.0330)	-0.5427	(0.0257)	-0.2680	(0.0176)
Wood manual	0.2052	(0.0384)	-0.7469	(0.0254)	0.4825	(0.0169)
Wood non-manual	0.0707	(0.0395)	-0.7243	(0.0280)	0.2722	(0.0153)
Paper manual	0.3413	(0.0358)	0.1475	(0.0380)	-0.1411	(0.0183)
Paper non-manual	-0.0141	(0.0448)	-0.9437	(0.0307)	0.5832	(0.0175)
Construction	-0.0751	(0.0315)	-0.1083	(0.0381)	0.6570	(0.0180)
Others	-0.0194	(0.0311)	0.0402	(0.0378)	0.3439	(0.0175)
Services	-0.0027	(0.0199)	-0.1135	(0.0241)	0.5053	(0.0152)
Manual	-0.0607	(0.0264)	-0.0551	(0.0324)	0.1478	(0.0171)
Clerical	0.0603	(0.0372)	0.5828	(0.0306)	-1.3417	(0.0105)
Upper	-0.0636	(0.0201)	-0.0661	(0.0254)	-0.4176	(0.0075)
South	-0.0577	(0.0690)	0.0010	(0.0821)	1.3345	(0.0113)
1980	-0.1270	(0.0090)	-0.0039	(0.0114)	-	
1981	0.1917	(0.0450)	-0.9277	(0.0277)	-	
1982	0.0708	(0.0452)	-0.9551	(0.0264)	-	
1983	0.0322	(0.0461)	-1.0114	(0.0250)	-	
1984	-0.0588	(0.0450)	-0.9817	(0.0236)	-	
1986	-0.1049	(0.0427)	-0.9064	(0.0228)	-	
1987	-0.1102	(0.0419)	-0.8714	(0.0226)	-	
1988	-0.1606	(0.0423)	-0.8854	(0.0227)	-	
1989	-0.1868	(0.0399)	-0.7984	(0.0224)	-	
1990	-0.1406	(0.0385)	-0.7490	(0.0224)	-	
1991	-0.1041	(0.0361)	-0.6575	(0.0225)	-	
1992	0.0730	(0.0389)	-0.7402	(0.0240)	-	
1993	-0.3734	(0.0379)	-0.6943	(0.0246)	-	
(Year-80)/10	-		-		0.8690	(0.0423)
(Year-80)^2/100	-		-		-1.7864	(0.0728)
(Year-80)^3/1000	-		-		0.6930	(0.0348)
$\rho_{\varepsilon AM}$	-1.7864 (0.0728)				-	
$\rho_{\eta AM}$	0.2156 (0.0614)				-	
$\rho_{\eta OM}, \rho_{\eta OA}$	0.2857	(0.0066)	0.0850	(0.0080)	-	
$\sigma_{\eta A}, \sigma_{\eta M}$	0.7420	(0.0117)	0.0305	(0.0462)	-	
Observations	65 310					
Log likelihood	-810 924					

Econometric Framework

Wages are ranked separately for each country for each year, and the ranks are normalized to the unit interval. The position of an individual in her/his first year in the sample is divided into quintiles. These are determined by the following latent and observed Origin wage equations:

$$O_i^* = Z_i\omega + \eta_i^o \tag{5.3}$$

$$O_i = \begin{cases} 1 & if \quad O_i^* \le 0.2 \\ 2 & if \quad 0.2 < O_i^* \le 0.4 \\ 3 & if \quad 0.4 < O_i^* \le 0.6 \\ 4 & if \quad 0.6 < O_i^* \le 0.8 \\ 5 & if \quad 0.8 < O_i^* \end{cases}$$

where O_i^* is the latent variable corresponding to Origin quintile O_i for individual i. Z_i is a matrix of individual characteristics, ω is a corresponding vector of coefficients and η_i^O is a random error.

Each year a number of individuals leave the sample due to retirement, sickness, unemployment, re-employment in a non-sampled unit, self-employment, etc. Nothing is known about the reason for attrition from the Finnish data, and so for the purposes of comparison we ignore the distinction between exit states, which we know from the Danish data. Strictly, the problem is one of non-response in that individuals may return to the sample after some time outside, but we use the generic term attrition for convenience. The attrition process is assumed to be determined by the following latent and observed equations:

$$A_{it}^* = Y_{it}\gamma + \eta_i^A + \varepsilon_{it}^A \quad \forall \quad O_i = 1 \tag{5.4}$$

$$A_{it} = \begin{cases} 0 & if \quad A_{it}^* \le 0 \\ 1 & if \quad A_{it}^* > 0 \end{cases}$$

where A_{it}^* is the latent variable corresponding to attrition from the sample A_{it} for individual i in year t. Y_{it} is a matrix of individual characteristics, γ is a corresponding vector of coefficients. ε_{it}^A and η_i^A are random errors, which may be thought of as respectively transitory and permanent components.

For all those who do not disappear from the sample in a given year we can observe their wage mobility. This is computed from the year-on-year difference in normalized ranks, and divided into 41 discrete categories. These are determined by the following latent and observed Mobility equations:

$$M_{it}^* = X_{it}\beta + O_i\delta + \eta_i^M + \varepsilon_{it}^M \quad \forall \quad A_{it} = 0, O_i = 1 \tag{5.5}$$

$$M_{it} = \begin{cases} -20 & if \quad M_{it}^* \le -0.195 \\ -19 & if \quad -0.195 < M_{it}^* \le -0.185 \\ & \quad \dots \\ -1 & if \quad -0.015 < M_{it}^* \le -0.005 \\ 0 & if \quad -0.005 < M_{it}^* \le +0.005 \\ +1 & if \quad +0.005 < M_{it}^* \le +0.015 \\ & \quad \dots \\ +19 & if \quad +0.185 < M_{it}^* \le +0.195 \\ -20 & if \quad 0.195 < M_{it}^* \end{cases}$$

where M_{it}^* is the latent variable corresponding to mobility M_{it} for individual i in year t. X_{it} is a matrix of individual characteristics, β is a corresponding vector of coefficients, O_i is an indicator of Origin quintile and δ is a corresponding coefficient. ε_{it}^M and η_i^M are random errors, which may be thought of as respectively transitory and permanent components.

Stochastic assumptions for the error terms are captured by the following variance-covariance matrix of a multivariate normal distribution:

$$V\begin{pmatrix} \varepsilon^M \\ \varepsilon^A \\ \eta^M \\ \eta^A \\ \eta^O \end{pmatrix} = \begin{pmatrix} 1 & . & . & . & . \\ \rho_{\varepsilon^{AM}} & 1 & . & . & . \\ 0 & 0 & \sigma_{\eta^M}^2 & . & . \\ 0 & 0 & \rho_{\eta^{AM}}\sigma_{\eta^M}\sigma_{\eta^A} & \sigma_{\eta^A}^2 & . \\ 0 & 0 & \rho_{\eta^{OM}}\sigma_{\eta^M} & \rho_{\eta^{OA}}\sigma_{\eta^A} & 1 \end{pmatrix} \tag{5.6}$$

The important point, as in all random effect models, is that the permanent effects are not correlated with the transitory, and furthermore are assumed uncorrelated with the explanatory variables. We do, however, allow correlation among the transitory effects and among the permanent effects themselves, in order to capture potential endogeneity (of Origin) and selectivity (of non-attrition) in both the short run and the long run.

The likelihood function for an individual is presented below

$$L_i = \int_{-\infty}^{+\infty}\int_{-\infty}^{+\infty}\prod_{t_i=1}^{T_i}\int_{O^{*-}}^{O^{*+}}\left[\int_{A^{*-}}^{A^{*+}}\int_{M^{*-}}^{M^{*+}}\phi_2(\varepsilon^A,\varepsilon^M)\,d\varepsilon^M d\varepsilon^A\right] \tag{5.7}$$
$$\bullet\frac{1}{\sigma_{\eta^A}\sigma_{\eta^M}}\phi_3\left(\frac{\eta^A}{\sigma_{\eta^A}},\frac{\eta^M}{\sigma_{\eta^M}},\eta^o\right)d\eta^O d\eta^M d\eta^A$$

where ϕ_2 and ϕ_3 represent respectively bi- and trivariate normal probability density functions. Essentially this is a trivariate ordered probit model for panel data. This is simplified (though more made messy than the standard case) by partial observability since mobility is not observed for those who disappear from the sample. Furthermore, since individuals are only observed for the first time once, the origin error term is only conditioned once per individual, so we do not have a transitory component in that error term.

The model is implemented in Gauss exploiting canned multivariate normal cdfs and numerically integrating out the random effects.

6. An Econometric Analysis of Low Pay and Earnings Mobility in Britain[1]

P.J. Sloane and I. Theodossiou

1 INTRODUCTION

The question of low pay has become a policy issue in a number of countries, especially those in which there has been a widening in the earnings distribution. This is the case in Britain where the Labour Party is committed to the introduction of a national minimum wage, though it has so far refused to commit itself to a particular figure on the grounds that this will be influenced by the prevailing economic circumstances. A number of trade unions have, however, argued for the minimum to be set at £4.10 per hour. This appears to be a relatively high figure. In the USA, for example, the minimum wage has recently been raised from \$4.25 to \$5.15 per hour, which would equate to £3.30. Indeed if one adjusted for the fact that earnings in the USA are higher than in Britain the comparable figure would be only £2.30 an hour, but the number of full-time workers earning below this figure in Britain is less than one per cent. There seems little purpose in setting a minimum wage so low that very few workers are affected. There is also the question of targeting those workers who are most in need of help. In this chapter we focus on earnings mobility, on the grounds that some workers may experience low pay only as a temporary phenomenon and, therefore, not be prime candidates for the support offered by a national minimum wage.

In an earlier study Sloane and Theodossiou (1996) utilized a multinomial logistic (MNL) regression to identify those individuals who fall into the low-pay category and who are unable to escape from it, using the first (1991) and third (1993) waves of the British Household Panel Study. However, the restrictions imposed by the so-called Independence of Irrelevant Alternatives (IIA) property required by the multinomial logit model are unappealing. In this chapter we extend our earlier analysis by utilizing a bivariate nested