Job Mobility in Britain: Are the Scots different? Evidence from the BHPS*

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Abstract

The Scottish extension-sample of the British Household Panel Study (BHPS) is used to shed light on differences in job mobility patterns in England and Scotland for both men and women. Based on probit estimates of the overall mobility rate, a decomposition is applied to distinguish between explained and unexplained differences. Furthermore, exploiting data on the number of job changes, a zero inflated poisson model is estimated to provide information on possible differences in the expected number of job changes. Overall, there is evidence that suggests significant differences in mobility patterns south and north of the Borders; however, this is confined to men. Hence, the results support a heterogeneous labour market policy for the two countries.

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1 Introduction

Since July 1st 1999, Scotland has had a devolved Parliament armed with numerous constitutional powers. Advocates of the devolution process put strong emphasis on existing differences between Scotland on the one hand and the rest of Britain on the other, in order to justify independent policies for the two countries. This paper sets out to find those differences in job mobility patterns south and north of the Borders two years after the first Scottish Parliament moved into place. The data is taken from the Scottish extension sample in the British Household Panel Study (BHPS) for wave nine (1999) and ten (2000).

Why do individuals switch jobs or occupations? Placing some trust into the rationality assumption, changes occur whenever individuals maximise their expected utility from doing so. An example may be the search for a better job match. Assume jobs are experience goods and, as such, their attributes are only revealed once the position has been taken (Jovanovic [10]). Thus, individuals may leave a firm or occupation in order to improve the match. Yet, since experience increases with age, job mobility is expected to be higher among younger individuals, decreasing with job tenure.

Specific human capital theory (e.g. Becker [1]) provides a rational why tenure and separation rates are negatively correlated. Over time, individuals gain knowledge on the job and thus increase their productivity. However, this human capital is partly specific to the task or firm and is consequently worthless in the wider labour market. Therefore, staying at the same firm is beneficial for both employee and employer, productivity gains are shared and voluntary quits and layoffs become less frequent.

However, not only labour supply impacts on job mobility. From the firms point of view, labour is an input and its quantity is determined by its costs. Hence, jobs are made redundant whenever the benefits, in terms of higher profits, exceed the costs of doing so. Booth et al. [3] bring forward various examples such as permanent exogenous shocks, skill obsolescence as a consequence of technological changes and downward rigidity of wages. Furthermore, they refer to institutional and cultural factors as sources of job changes.

Several studies have analysed job mobility and occupational changes in Britain. The majority of them have focused on specific sub-groups of the population or aspects of mobility. For example, Harper [8] uses data from the National Training Survey on occupational mobility of British males. Owen and Green [14], on the other hand, shed light on labour market experience and occupational changes amongst ethnic groups, applying Labour Force Survey data. Drawing from the same source, Gregg and Wadsworth [7] highlight patterns in job tenure, turnover and security from the mid seventies until the early nineties. Furthermore, Dalton and Kidd [5] investigate the relationship between different forms of human capital investments and their impact on job and occupational mobility. Finally, and of particular interest for this paper, are the studies by Booth and Francesconi [2] and Booth et al. [3], as both apply data from the BHPS.

Although difficult to compare in terms of data and methodology, some general results can be derived from the above studies. First, young people are far more likely to change jobs and, even more pronounced, job tenure significantly reduces mobility. Second, women exhibit higher average quit and promotion rates as compared to men. However, controlling for various characteristics, differences shrink. Third, over time, male and female mobility patterns in Britain have become more similar. Finally, investment in specific human capital reduces job turnover while investment in occupational specific human capital increases the probability of job and occupational change. Yet, thus far there has little work been done on regional differences in mobility patterns, most likely due to a lack of representative data.

This paper is structured as follows. The next section will briefly discuss the BHPS and the sample. Second, overall job mobility in England and Scotland is modelled. Third, results are decomposed in order to distinguish differences due to labour market structure and employees characteristics. Finally, the determinants of the number of job changes are analysed for the two countries.

2 The Data

As a matter of course, a sound analysis of job mobility requires information on individuals employment history over time. The BHPS is one such source. Since its introduction in 1991, every year over $5,000$ households made up of roughly $10,000$ individuals are interviewed. While it has always been a nationally representative sample, only recently extension samples for Scotland and Wales have been launched, aiming to increase the relatively small sample size - approximately 500 households in each country - to $1,500$ households. The main objective has been to enable independent analysis of the two countries on a representative level.

The BHPS provides information on the timing of job changes within the last 12 months. At each interview, individuals are asked to report whether their current job has been taken up before or after the previous interview. Additionally, the number of changes are recorded. Even though there is information on whether the job change occurred due to a voluntary quit, a promotion within the same firm or a layoff, the number of observations from this sub-sample is too small to make statistical inference feasible.

For the purpose of this paper the sample contains only individuals which are, at the date of the interview, full-time employees, aged 16 to 64, not self-employed, working in agriculture or for the armed forces and for which information is available for both wave nine (September 1999) and ten (September 2000). Furthermore, only individuals residing in England or Scotland have been included. The various dependent variables are constructed using answers given in wave ten's interview, while covariates are derived from the information prior to job changes in wave nine. The resulting cross-section data consist of $2,443$ males and $1,785$ females of which 605 (478) are Scottish. In the following, two sub-samples are used for the various analyses.

Additionally to the BHPS, data on regional unemployment rates provided by the Office for National Statistics [13] have been merged into the cross-section. Note, however, that only the aggregate unemployment rate for Scotland has been included without any further disaggregation.[1]

3 Overall job mobility

3.1 Econometric model and descriptive statistics

The overall mobility rate in the sample encompasses quits, promotions and layoffs.[2] Each individual is asked whether their current job was attained before or after the previous interview date 12 months ago, where in the former the individual is classified as stayer and in latter as changer. The decision to change job is determined by personal and regional characteristics. In particular, assume that the mobility rate y_i^* of individual i can be expressed as

$$y_i^* = x_i^{\prime}\beta + \varepsilon_i,$$

where x_i is a vector of personal and regional characteristics, β the vector of coefficients to be estimated and ε_i the residual. In the case of a probit model these are assumed to be normally and independently distributed.

Since the mobility rate y_i^* is unobserved and the data only contains information on whether an individual has changed jobs in the last 12 months, a binary choice model is employed, where

$$\begin{aligned} y_i &= 1 \;\; if \;\; y_i^* > 0 \\ y_i &= 0 \;\; if \;\; y_i^* \leq 0, \end{aligned}$$

where y_i is a dummy variable which takes on the value of 1 if the individual has changed jobs and 0 otherwise. Applying standard maximum likelihood estimation, the vector of $\hat{\beta}$s can be derived for the above model.

The following covariates have been included in the vector $x_i^{\prime}$ on the basis of significance and contribution to the model's performance: Age, marital status, number of children, level of job satisfaction, annual labour income, job tenure in years, skill level, firm size, dummies for employment sector and industry, general training and local unemployment rates. A detailed description of the full set of variables is given in the appendix. The mean characteristics are reported in tables 1 and 2.

[1] Given the information provided in the BHPS, disaggregation on Local Authority District level is possible. However, the number of observations in each Scottish district becomes fairly small.

[2] Whether this is a valid model specification can be formally tested by fitting a model that distinguishes promotions, quits and layoffs and tests successively whether the pooling of stays and promotions on the one hand and quits and layoffs on the other hand is an appropriate one. The test amounts to a simple log likelihood test (Cramer and Ridder [4]). However, since such a disaggregation is not yet feasible it must be left for future analysis once more than two waves are available. Note, therefore, that in the present model promotions, quits and layoffs are treated as one category.

Mobility in the sample is remarkably high. On average, 28 per cent of English males changed jobs in the sample period as compared to 26 per cent in Scotland. For women, the difference is slightly more pronounced (29 to 26 per cent). Booth and Francesconi [2] report similar numbers using a longitudinal sample of the BHPS. Unsurprisingly, the percentage of movers in the age group 16-20 is significant compared to the overall share of this group in the sample. About 4 per cent of the Scottish sample is aged 16-20, while almost 8 per cent of job changers are in this age group. Again, a similar picture arises for women. On the other hand, the mobility rate amongst individuals aged 56 to 64 in England is only 3 per cent, while their total share in the sample is twice as high (not reported). A negative relationship between age and mobility is well documented in the literature (see above). For example, Gregg and Wadsworth [7] find for Britain in the time 1975-93 that half of all job changes occur before the age of 30 and a quarter before the age of 20; Topel and Ward [16] find even higher numbers for the United States.

Yet, even stronger is the impact of job tenure on mobility. As tables 1 and 2 show, job changers are only half as long attached to a job or firm as compared to the overall sample, regardless of sex or country. However, note that Scottish employees exhibit far higher attachment rates than their counterparts south of the Borders.

There is only a slight difference in mean characteristics for changers and stayers in terms of their mean annual labour incomes, the number of young children, marital status, general training and most surprisingly, job satisfaction. However, there are significant differences in the sectoral distribution among sexes on the one hand and countries on the other. About 40 per cent of Scottish women in the sample are employed in the public sector and almost 30 per cent of job changers originate from this group. The relative share among movers is even higher for English women (24 per cent). In contrast, men are less likely to be employed in the public sector in England and Scotland (14 and 22 per cent, respectively).

Similarly, there are hardly any differences in the characteristics for the two groups in the occupational variable. Tables 3 and 4 report mobility matrices for males and females within five occupational classes. Clearly, most of the changes occur within rather than between occupations. But it also highlights the point that mobility occurs in both directions, up and down the occupational ladder.

Additionally, firm size seems to impact on job mobility. Independently of sex or country, the percentage of changers employed in firms with less than 50 employees lies between 40 and 53 per cent. This is not overly surprising, given that around 90 per cent of all enterprises in England and Scotland fall in this range. Furthermore, men employed in the energy sector (SIC-1) are far more likely to change jobs in Scotland than they are in England (8 and 2.5 per cent, respectively). The same applies to women, while the overall numbers are smaller. Tables 5 and 6 report the mobility matrix for males and females within nine industries. Once again, most of the mobility occurs within rather than between different industries, similar to the results on occupational mobility.

Note that Scottish changers have a substantially higher number of children aged 12 to 18. Furthermore, men changing jobs in England and Scotland have a significantly greater number of young children as compared to their average female counterparts. However, this does not seem to be related to age differences. On average, the distribution of age and number of children aged 4 to 11 is very similar for men and women.

3.2 Estimation Results

The parameter estimation results for the binomial probit are reported in tables 7 and 8. The first three columns refer to the pooled estimation of English and Scottish males and females respectively. As the interpretation of the standard coefficients is difficult, marginal effects, $\frac{\partial p(x)}{\partial x_i}$, have been reported as well.[3]

First, being young significantly increases the likelihood of a job change for both males and females. For example, the mobility probability for an average male in the age group 16 to 20 is increased by around 19 per cent and for women by 12 per cent, other things equal. Again, this is not surprising and perfectly in line with other studies.

Second, and equally unsurprisingly are the results for job tenure. Both coefficients are significant at the 1 per cent level and negative i.e. the greater the attachment to the current job or firm, the lower the separation probability. Again, this is a well known stylist fact in the mobility literature (Jovanovic [10], Topel and Ward [16], Booth et al. [3]). Note, however, that the negative relationship is decreasing in time as the significant and positive coefficient on the squared covariate shows. Most studies also find a strong and significant negative effect on labour market experience and job mobility, yet, these variables are constructed using information on the entire labour market history which is not yet available for the Scottish sample in the BHPS. However, as Booth and Francesconi [2] remark, most of this effect is likely to be due to the negative relationship between age and mobility.

Third, having small children increases significantly the probability for males to change jobs but has no noticeable influence on the female mobility rate, other things equal. Recall from the sample characteristics that female movers seem to have fewer children in this range on average as compared to men. This might indicate that mobile women postpone family decisions until a good job match has been found. Booth and Francesconi [2] find in their study on gender differences a negative and mostly significant relationship between the number of young children and job mobility for both men and women.

Finally, the separation probability appears to be a negative function of job satisfaction; the higher the satisfaction in the current position, the less likely will an individual leave the job. General training on the other hand increases the likelihood of job changes, as well as being employed in a small firm. Both

[3] Note that for roughly continuous covariates the marginal effect is $\frac{\partial p(.)}{\partial x_i} = \phi(\bar{x}\hat{\beta})\hat{\beta}_i$, where $\phi(.)$ is the pdf of the standard normal distribution. However, for binary explanatory variables the marginal effect for a change in, for example x_1 from 0 to 1, is $\Phi(\hat{\beta}_0 + \hat{\beta}_1 + ... + \hat{\beta}_k \bar{x}_k) - \Phi(\hat{\beta}_0 + ... + \hat{\beta}_k \bar{x}_k)$, where $\Phi(.)$ is the cdf of a standard normal distribution.

effects are significant. Surprisingly, dummies on industry and sector exhibit no significant impact on mobility, even though they contribute to the overall performance of the model. Not reported but included at an earlier stage, various education variables had no significant effect on the dependent variable or the performance criteria.

Since voluntary job changes ought to increase utility, one would expect a negative relationship between past labour income and the probability of job changes as wages are usually an important part of the perceived utility. On the other hand, if some of the lifetime mobility has already happened prior to the current move, high wages might be a proxy for a higher than average mobility rate; the total effect might be, therefore, ambiguous. Harper [8], for example, finds in a study on male occupational mobility in Britain a negative relationship between hourly wages and mobility. While this is the case for women as table 8 shows, there is no statistically significant effect of the annual labour income on mobility for men, other things equal.[4]

Regional unemployment rates lower the probability of job changes; however, the coefficient is insignificant and very small.

In order to test whether there are structural differences in job mobility patterns between England and Scotland, the last three columns in tables 7 and 8 report the estimated parameters for a pooled probit including a country dummy for Scotland along with interaction terms for the full set of covariates. Again, marginal effects have been reported to ease the interpretation of the coefficients.

The above results on almost all variables remain very robust for both males and females. Note, however, the sign switch on the constant term for Scotland; while the effect is significant and positive (insignificant and positive) for males (females) in the pooled regression with homogenous slope parameters, it turns out to be negative and significant once one allows for heterogeneities in coefficients. Note also the increase in the magnitude of the marginal effect for both males and females.

Being male and Scottish reduces the probability of a job change by 33 per cent, as the marginal effect on the Scottish intercept term indicates. Although few interaction terms are significant, the assumption that all coefficients have the same impact on the job mobility rate of males in England and Scotland can be rejected at less than 5 per cent ($\chi^2(15) = 25.17$); this suggests that there are indeed structural differences in job mobility behaviour north and south of the Borders.

Beside the intercept term, coefficients on the annual labour income, occupation and number of older children are, individually, significantly different from England. Note that their magnitude in terms of marginal effects is very similar.

[4] Note that ideally one wants to measure the expected utility difference between current and future position. However, using income differences to this end is flawed due to fact that cause and effect are indistinguishable. For example, once one observes a higher wage in the new job or occupation, mobility has already occurred and the new wage is due to the mobility, while mobility was due to a higher expected wage or wage offer. The latter, however, is usually not observed.

Secondly, the fact that involuntary separations are included in the sample might off-set part of the effect.

The result suggests that compared to their English counterparts, Scottish males with higher labour incomes over the previous year exhibit a higher mobility rate; similarly, men working in unskilled occupations or with a larger number of older children, are less likely to change jobs, other things being the same. Furthermore, the joined significance test for the number of children is not rejected ($\chi^2(2) = 4.36$). The same applies for the joint test on firm size, sector and industry ($\chi^2(3) = 3.01$).[5] Robustness checks show that these results remain valid even when insignificant variables such as the remaining occupational groups are included.

In contrast, the picture looks distinctively different for women. The only term that is individually significant, apart from the intercept dummy, is the coefficient for annual labour income. It is therefore unsurprising that the joint significance test cannot be rejected ($\chi^2(15) = 9.52$). Note, that even though on average mobility rates for men and women are very similar, results suggest that the underlying determinants vary by gender.

3.3 Decomposition of fitted mobility probabilities

Results suggest that similar characteristics in the two countries translate significantly differently into male mobility rates. The parameter estimates from the pooled regression, including an intercept term and the full set of Scottish interaction terms in tables 7 and 8, are equivalent to two separate regressions for England and Scotland; table 9 reports the results for the male sample. Note that for obvious reasons neither the dummy for London nor the regional unemployment rates have been included; however, the homogeneity assumption for the slope parameters is still rejected. Based on the results in table 9, the conditional mobility probability for England is $P(y_i = 1|x_i) = 28.45$ and for Scotland 27.24 per cent

To understand what drives the lower mobility rate in Scotland, a disaggregation into components that account for differences in personal characteristics as well as differences in the labour market structure can be done. The technique is based on Jones and Makepeace's [9] ordered probit decomposition, which has been applied to the binomial case by, for example, Pagán and Tijerina-Guajardo [15]; formally

$$\begin{aligned}\bar{M}_E - \bar{M}_S &= \left[1/N_E \sum_{i=1}^{N_E} \Phi\left(x_{i,E}'\hat{\beta}_E\right) - 1/N_S \sum_{i=1}^{N_S} \Phi\left(x_{i,S}'\hat{\beta}_E\right)\right] \\ &+ \left[1/N_S \sum_{i=1}^{N_S} \Phi\left(x_{i,S}'\hat{\beta}_E\right) - 1/N_S \sum_{i=1}^{N_S} \Phi\left(x_{i,S}'\hat{\beta}_S\right)\right] \qquad (1)\end{aligned}$$

where $\bar{M}$ is the fitted conditional probability for England and Scotland respectively, x_i is the matrix of characteristics, $\hat{\beta}$ the vector of estimated coefficients

[5] Differences are even larger when part-time employees are included, where the Scottish interaction term indicates that part-time employees in Scotland are significantly more mobile (results are not reported).

for the two countries, N is the number of respective observations and Φ the cumulative distribution function for a standard normal distribution.[6]

The interpretation of equation (1) is very similar to the linear regression model decomposition pioneered by Oaxaca [12]. The term on the left-hand side is the difference in predicted mobility rates in England and Scotland. The first component in square brackets on the right-hand side is the difference in mean mobility rates due to differences in the characteristics of English and Scottish employees. The second component captures the differences in mean predicted mobility rates due to differences in the estimated vector of coefficients, $\hat{\beta}$. Hence, under the probit assumptions, the first right-hand side component represents the explained and the second term the unexplained variation in the sample, so that equation (1) can be rewritten as

$$\bar{M}_E - \bar{M}_S = \psi - \varphi$$

where ψ is the explained and φ the unexplained part.

Following Even and Macpherson [6] it is possible to further disaggregate equation (1) into j sub-components despite the non-linearity of the probit model:

$$\psi_j = \psi \times [(\bar{x}_{E,j} - \bar{x}_{S,j})\,\hat{\beta}_{E,j}]/[(\bar{x}_E - \bar{x}_S)'\,\hat{\beta}_E] \tag{2}$$

and

$$\varphi_j = \varphi \times [\left(\hat{\beta}_{E,j} - \hat{\beta}_{S,j}\right)\bar{x}_{S,j}]/[\left(\hat{\beta}_E - \hat{\beta}_S\right)'\bar{x}_S] \tag{3}$$

where equation (2) represents the fraction of explained differences in (1) due to differences in the jth mean characteristic; similarly, equation (3) is the fraction of the unexplained part in (1) that is due to differences in the jth coefficient. By construction, $\sum_j \psi_j = \psi$ and $\sum_j \varphi_j = \varphi$. As a consequence, the fraction explained by the jth component (characteristic or coefficient) is directly related to the change in mean values of x and the parameters β.

Table 10 reports the results for both the decomposition in equation (1) and equations (2) and (3). The overall difference in the predicted mobility rates between England and Scotland is roughly 1.2 percentage points. In comparison to other regions such as Wales where the predicted gab in mobility based on the above model is around 3 percentage points, this appears to be rather small.

Yet, this gap would be up to 3.4 percentage points if one were to consider only differences in observable characteristics. On the other hand, differences in the labour market structure (i.e. differences in the slope parameters) off-set this effect, causing a reduction in the overall difference. That is, given the characteristics of English and Scottish employees in the sample, the difference between the mobility rates would be quite substantial. However, due to differences in the labour market structure in the two countries, the difference is modest. As

[6] Note that $\hat{\beta}_E$ in the first term on the right hand side can equally be replaced by $\hat{\beta}_S$ and similarly, $x_{i,S}$ in the second term can be replaced by $x_{i,E}$. Both methods are equally valid and will in general produce different results.

the pooled parameter estimates for males show, this difference is statistically significant.

The bottom-half of table 10 provides information on the strength of the impact of individual mean characteristics and coefficients. Results suggest that differences in the age structure, marital status, employment sector, training and job tenure between England and Scotland are responsible for the positive gap in mobility rates. For example, differences in job tenure characteristics of employees increase the gap by 7.4 percentage points. This is not very surprising, recalling that Scottish males exhibit higher job and firm attachment on average than their English counterparts. Yet, the positive effect is partly off-set by differences in job satisfaction, industry and occupation as well as the number of children aged 12 to 18.

The second column in the bottom-half shows the disaggregation of differences in the coefficients. Most of the overall negative impact on the difference in the mobility rate is explained by differences in the coefficients for job satisfaction, annual labour income, age, marital status and the number of older children. On the other hand, differences in the coefficients on job tenure, occupation, sector and young children contribute to a positive overall gap.

The most pronounced impact, however, is captured in differences in the coefficient of the constant terms; it reflects both structural differences and personal characteristics that have not been captured in the set of covariates. Given that almost all exogenous variables control for the latter, one may conclude that some structural differences in the labour market between England and Scotland push mobility rates apart, other things equal. Since the term on the intercept and the log annual labour income off-set one another in magnitudes, it seems that no single difference of coefficients drives the results. This is supported by the fact that once the log annual labour income is removed from the regression, results remain robust.

Finally, note that replacing the bases in equation (1), i.e. $\hat{\beta}_E$ with $\hat{\beta}_S$ and $x^{\prime}_{i,S}$ with $x^{\prime}_{i,E}$ does not change the principal results. Yet, the explained and unexplained components are even larger and the reported figures in table 10 are therefore lower bound predictions.[7]

4 Number of job changes

4.1 The count model

Thus far, the focus has been on the overall probability for a job change to occur. However, it might be equally interesting to study the determinants of the expected number of changes. The BHPS contains the number of separate jobs held in the reference year, including different jobs with the same employer and self-employment spells.[8] Since these are successively held jobs, the number

[7]While the overall mobility gab remains the same by definition, the difference due to differences in characteristics and coefficients increases to 4.5 and 3.3 per cent, respectively.

[8]Note, however, that the sample is still restricted to those individuals who are not self-employed at either interview date.

of actual job changes within the 12 months period 1999 to 2000 can be derived.

Several possible count models are available to estimate the determinants of the number of changes of which the simplest is the Poisson model, where mean is equal variance.[9] Yet, this model fails to account for heterogeneity among individuals in the rate of the count variable known as overdispersion. Table 11 indicates, however, that the variance of the number of changes significantly exceeds the mean. As a consequence, Poisson estimates are likely to be consistent but inefficient, leading to downward biased standard errors and inflated z values. The class of negative binomial regression models circumvents this unpleasant property by replacing the mean with a random variable.

Furthermore, as there is evidence that the decision to stay is driven by a different process as compared to the decision to change job, a zero modified count model seems appropriate where the production of zero counts (stays) is explicitly modelled. The probability to change jobs may differ among individuals; some are more likely than others to change (e.g. young employees) but some may never change in the period under consideration (e.g. due to fixed contracts). For the latter group, the probability of zero is unity. Thus, the probability of being among the stayers is a combination of the probability for a zero count in the two groups times the probability of being in that particular group.

Let ρ_i be the probability for individual i being in the group of stayers and $(1-\rho_i)$ the probability that the individual exhibits a positive number of job changes. Then, combining the negative binomial and the zero count model leads to a zero inflated negative binomial model (ZINB), which is based on a simple Poisson distribution; namely

$$\Pr(y_i = 0|x_i) = \rho_i + (1-\rho_i)\exp(-\tilde{\lambda}_i) \tag{4}$$

$$\Pr(y_i|x_i) = (1-\rho_i)\frac{\exp(-\tilde{\lambda}_i)\tilde{\lambda}_i{}^{y_i}}{y_i!} \quad \text{for } y_i > 0 \tag{5}$$

where y_i is the count variable equal to zero if the individual does not change jobs; otherwise, any positive value indicates the number of job changes within the 12 months period. The random variable $\tilde{\lambda}_i$ is defined as $\tilde{\lambda}_i = \exp(x_i^{\prime}\beta + \varepsilon_i)$ and secures that heterogeneities are accounted for.[10] The probability ρ_i is determined by a logit model, $\rho_i = \mathsf{Z}(x_i^{\prime}\beta)$, where Z is the logit cumulative distribution function. Hence, equation (4) is the weighted conditional probability of being in the zero group of stayers while equation (5) is the conditional probability of exhibiting a positive number of job changes.

4.2 Some descriptives

As the sample of the number of changes is slightly different from the sample used to determine overall job mobility, table 11 reports mean characteristics for

[9] The standard Poisson regression model is $\Pr(y_i|x_i) = \frac{\exp(-\lambda_i)\lambda_i^{y_i}}{y_i!}$ where λ_i is the expected value of y given x, $\lambda = E(y|x) = \exp(x^{\prime}\beta)$.

[10] For a detailed derivative see Long [11].

the sample in this section. In total, data on $2,347$ males and $1,688$ females is available of which 571 (456) are Scottish. Compared to tables 1 and 2, differences are very small and mainly confined to characteristics such as sector and number of children.

On average, the number of job changes is low, with the mass clearly on zero for both males and females. This is particularly pronounced for Scottish men who change jobs 0.2 times a year as compared to 0.3 times for their English counterparts. For women the difference is smaller. Note that the numbers for English males correspond with the average overall probability for a job change while this is not the case for women or Scottish males (compare tables 1 and 2).

The maximum number of changes in the sample is 4; for both men and women, roughly 77 per cent do not change jobs, up to 20 per cent change once and 3 per cent twice within the 12 months. Note that at either interview date individuals are required to be employed full-time in order to enter the sample. However, there is no such restriction for the jobs held in between.

4.3 Results

Surprisingly, fitting the ZINB suggests that there is no overdispersion despite evidence from the descriptive data. The one-tailed z-test does not reject the null for equidispersion by any standard.[11] Hence, the random variable $\tilde{\lambda}_i$ in (4) and (5) is replaced by $\lambda_i = \exp(x_i^{\prime}\beta)$, i.e. mean is equal variance and individuals with the same x have the same expected conditional count λ. The model becomes a zero inflated Poisson regression (ZIP) instead. Table 12 reports the parameter estimates for both males and females from the pooled ZIP regression using the same set of covariates. The logit has been fitted for an intercept term only and results are not reported; yet, the fitted probability of always being in the zero group, ρ, is extremely slim and women are slightly more likely to be in this group.

Clearly, the results resemble the estimates on the overall job mobility. Being young, male and living in England increases the expected number of job changes by 58 per cent, other things equal, while the overall mobility probability increases by only 19 per cent (see table 7).[12] Similarly, working in a small firm increases the expected number of jobs by 24 per cent. Since the Scottish coefficients are both insignificant these figures apply for employees north of the Borders as well.

On the contrary, being employed in the public sector significantly decreases the number of jobs in the 12 month period by roughly 20 per cent; job tenure and job satisfaction reduce it by 18 per cent each, other variables constant. While the number of older children seems to have no significant impact on the overall

[11] In particular, the conditional variance in the ZINB model is $Var(y_i|x_i) = \lambda_i(1 + \alpha\lambda_i) = \lambda_i + \alpha\lambda_i^2$. The z-test amounts to test whether α is zero in which case the variance simplifies to the mean; namely $Var(y_i|x) = \lambda_i$.

[12] The percentage change in the expected count for a unit change in x_j is $100 \times [\exp(\beta_j \times 1) - 1]$. For example, in the binary case, being male and in the age group 16-20, equals a change in x from zero to one and; hence, $100 \times [\exp(0.456 \times 1) - 1] = 57.77$.

mobility rate, it does significantly reduce the number of job changes in England. Yet, being male and Scottish increases the expected number significantly and the net effect results in an approximately 27 per cent increase.

Recall that marital status did not affect overall mobility. It does, however, significantly lower the expected number of jobs by 19 per cent. On the other hand, annual labour income is insignificant as well as the English coefficient for occupation. Unemployment rates, again, do not significantly affect mobility patterns, a pretty robust result, as various other variable definitions have been tried and failed to show a significant impact as well.

Being male and Scottish decreases the expected number of job changes by up to 93 per cent which is only partly outweighed by other coefficients. Even though only two interaction terms are individually significant, the hypothesis that all Scottish male coefficients are jointly zero, is rejected at the one per cent level ($\chi^2(14) = 29.36$). But again, this is not the case for women ($\chi^2(14) = 7.34$); the overall model performance with only a handful significant variables indicates once more that gender does matter in terms of mobility patterns. The results also suggest that there are no differences south and north of the borders but there are within countries.

Comparing observed with predicted mobility probabilities suggests a rather good fit of the model both for men and women. In the sample, the conditional male probability of not changing jobs between September 1999 and September 2000 is $\Pr(y_i = 0|x_i) = 0.78$, while the conditional probabilities for one and two switches are 18 and 3 per cent respectively. For women the three probabilities are very similar.

In general, the model specification can be tested using a likelihood ratio test advised by Vuong [17]. Yet, since a robust estimation procedure has been applied, tests based on log likelihood values are not appropriate. Thus, to test the robustness of the parameter estimates, table 13 reports the results for the alternative Poisson specification. Obviously, the results are very similar and the hypothesis of homogenous coefficients is still be rejected at the one per cent level.

5 Conclusion

The Scottish extension-sample of the BHPS has been used to shed light on differences in mobility patterns in England and Scotland. Both the overall job mobility, including voluntary and involuntary separations, and the number of job changes within the 12 month period September 1999 to September 2000 have been modelled. Results suggest that significant differences north and south of the Borders do exist.

Overall job mobility in the two countries is driven by well known determinants such as age, job tenure and gender and is therefore in line with results from other studies. However, there is evidence that mobility patterns in Scotland are significantly different compared to England; similar characteristics of the two countries translate significantly differently into job mobility.

Second, and most importantly, even though overall predicted mobility rates are fairly similar, further disaggregation in explained (characteristics) and unexplained (coefficients) components shows that the underlying mobility structure is quite distinct. Differences in characteristics tend to widen the gap in predicted mobility rates substantially, i.e. were the Scottish and English labour market structures similar, mobility would be relatively and substantially lower north of the Borders. On the other hand, differences in the labour market structure counter-balance differences in characteristics, closing the gap in mobility rates. That is, were individuals in Scotland and England similar in their characteristics, Scotland would have a higher relative mobility rate. Yet, as the net effect remains positive, higher mobility rates in England are due to characteristics of the workforce despite the relatively less favourable labour market structure.

Third, the BHPS also provides information on the number of job changes. Using a zero inflated Poisson model, results suggest that there are again differences between Scotland and its neighbour which are even stronger than differences in the overall mobility. Being Scottish significantly and quite substantially reduces the number of expected jobs held over the 12 months period.

Furthermore, the picture looks distinctively different for women. Neither are their differences in overall mobility patterns, nor is the number of job changes significantly different from the ones south of the Borders. The results indicate that the fitted male model does not seem to suit female mobility patterns. Hence, gender does matter, as has been established elsewhere.

Finally, theory predicts that mobility helps to adjust imbalances in the labour market such as unemployment rates. Yet, results suggest that past unemployment rates do not significantly affect mobility in the sample, although the direction of its effect seems appropriate.

Yet, the above results should be treated as indicative since a more detailed disaggregation into different separation reasons is not yet feasible but is certainly desirable. With more information arriving from wave to come, this is a temporary problem.

Putting the results into policy perspective, it has been argued that the devolution process rests its existence - among other things - on the need to address economic problems on a regional, rather than national level. Results in this paper suggest that there are indeed differences at the outset of the devolution both in terms of structure and characteristics; while the structure fosters mobility, Scottish characteristics hamper it. Restricting the analysis solely on the overall mobility rate is therefore misleading.

A sound labour market policy ought to be altering the structure in accordance to economic needs. Yet, these needs are not addressed in the paper and in order to derive policy implications from the above results the crucial question is whether the mobility rate in Scotland is appropriate? Taking the higher than average unemployment rate as a crude measure, it might not be.

Nevertheless and independent of whether the Scottish labour market is flexible enough, the fact that Scots appear to be different - both in terms of labour market and individual characteristics - provides some support for an independent labour market policy. Furthermore, gender issues arise from the above results; yet, they have been found within rather than between countries.

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Variable	England: Job changers	England: All	Scotland: Job changers	Scotland: All
Mobility rate		0.2841		0.2692
		(0.4511)		(0.4439)
Age 16-20	0.1102	0.0567	0.0764	0.0411
	(0.3134)	(0.2313)	(0.2665)	(0.1988)
Age 21-30	0.2994	0.2280	0.2847	0.2112
	(0.4585)	(0.4197)	(0.4529)	(0.4086)
Married	0.4886	0.5848	0.5417	0.6112
	(0.5004)	(0.4929)	(0.5000)	(0.4879)
Children 4-11	0.5052	0.4879	0.5347	0.4879
	(0.8219)	(0.8118)	(0.8683)	(0.8298)
Children 12-18	0.1975	0.2132	0.2917	0.2224
	(0.4921)	(0.5053)	(0.6016)	(0.5093)
Job satisfaction	4.8690	5.1571	4.9375	5.0729
	(1.5537)	(1.3615)	(1.5964)	(1.4954)
Training	0.3825	0.3260	0.3125	0.2411
	(0.4865)	(0.4689)	(0.4651)	(0.4282)
Log annual income	9.4947	9.6539	9.6337	9.6515
	(0.8558)	(0.6801)	(0.7710)	(0.6431)
Job tenure	2.5054	4.8260	3.6849	6.5642
	(3.9114)	(5.9334)	(5.7368)	(7.4561)
Unskilled	0.1726	0.1713	0.1597	0.1607
	(0.3783)	(0.3769)	(0.3676)	(0.3676)
Firm size < 50	0.4574	0.4211	0.3958	0.4019
	(0.4987)	(0.4939)	(0.4907)	(0.4907)
SIC-1	0.0249	0.0254	0.0833	0.0505
	(0.1561)	(0.1574)	(0.2774)	(0.2191)
Public	0.1019	0.1447	0.1319	0.2150
	(0.3028)	(0.3519)	(0.3396)	(0.4112)
Unemployment rate	5.5834	5.6303		
	(1.6310)	(1.5979)		
N	481	1693	144	535

Table 1: Mean characteristics for English and Scottish males. Standard devidations in parentheses. Cross-section weights applied.

Variable	England Job changers	England All	Scotland Job changers	Scotland All
Mobility rate		0.2920		0.2635
		(0.4549)		(0.4411)
Age 16-20	0.1349	0.0736	0.0982	0.0494
	(0.3421)	(0.2613)	(0.2989)	(0.2170)
Age 21-30	0.3284	0.2466	0.3214	0.2447
	(0.4703)	(0.4312)	(0.4691)	(0.4304)
Married	0.3695	0.4752	0.4464	0.5035
	(0.4834)	(0.4996)	(0.4994)	(0.5006)
Children 4-11	0.2991	0.3134	0.3393	0.2988
	(0.6027)	(0.6580)	(0.6086)	(0.6239)
Children 12-18	0.1994	0.2123	0.2946	0.2353
	(0.4983)	(0.5247)	(0.6244)	(0.5374)
Job satisfaction	5.0000	5.3074	5.0982	5.3388
	(1.5166)	(1.3468)	(1.5766)	(1.3132)
Training	0.3988	0.3853	0.3393	0.2682
	(0.4904)	(0.4869)	(0.4756)	(0.4436)
Log annual income	9.1282	9.2892	9.1367	9.2881
	(0.8383)	(0.7892)	(0.8441)	(0.7595)
Job tenure	2.1862	4.0200	2.2619	4.8607
	(2.9028)	(4.8540)	(2.9659)	(5.5647)
Unskilled	0.1085	0.1190	0.1696	0.1506
	(0.3115)	(0.3239)	(0.3770)	(0.3581)
Firm size < 50	0.4545	0.4521	0.5268	0.4871
	(0.4987)	(0.4979)	(0.5015)	(0.5004)
SIC-1	0.0117	0.0077	0.0268	0.0141
	(0.1078)	(0.0875)	(0.1622)	(0.1181)
Public	0.2434	0.3142	0.2946	0.3976
	(0.4298)	(0.4644)	(0.4579)	(0.4900)
Unemployment rate	5.5774	5.6757		
	(1.6073)	(1.6245)		
N	341	1168	112	425

Table 2: Mean characteristics for English and Scottish females. Standard devidations in parentheses. Cross-section weights applied.

From / *Occupation* (*To*)	Occ -1	Occ -2	Occ -3	Occ -4	Occ -5	*N*
Occ-1	53.06	30.61	8.16	4.08	4.08	49
Occ -2	4.95	69.82	9.91	10.36	4.50	222
Occ -3	4.08	25.51	56.12	8.16	6.12	98
Occ -4	1.91	5.73	5.73	67.52	18.47	157
Occ -5	0.00	11.01	12.84	30.28	45.87	109

Table 3: Mobility matrix of male job changers in five different occupational categories; namely professional, managerial, non-manual skills, manual skills and unskilled, respectively. Cross-section weights applied.

From / *Occupation* (*To*)	Occ -1	Occ -2	Occ -3	Occ -4	Occ -5	*N*
Occ-1	62.50	18.75	6.25	12.50	0.00	16
Occ -2	2.25	76.97	15.17	2.81	2.81	178
Occ -3	0.57	22.41	67.82	3.45	5.75	174
Occ -4	0.00	16.22	8.11	43.24	32.43	37
Occ -5	0.00	11.86	25.42	8.47	52.54	59

Table 4: Mobility matrix of female job changers in five different occupational categories; namely professional, managerial, non-manual skills, manual skills and unskilled, respectively. Cross-section weights applied.

From	To Industry	SIC-1	SIC-2	SIC-3	SIC-4	SIC-5	SIC-6	SIC-7	SIC-8	SIC-9	*N*
	SIC-1	50.00	4.17	8.33	8.33	8.33	0.00	8.33	8.33	0.00	24
	SIC-2	0.00	57.14	19.05	9.52	0.00	9.52	4.76	0.00	0.00	21
	SIC-3	2.47	3.70	67.90	7.41	2.47	4.94	0.00	8.64	2.47	81
	SIC-4	0.00	3.03	12.12	54.55	4.55	10.61	7.58	4.55	1.52	66
	SIC-5	2.38	0.00	11.90	11.90	57.14	2.38	4.76	4.76	4.76	42
	SIC-6	0.88	0.00	3.54	3.54	0.88	65.49	8.85	7.08	8.85	113
	SIC-7	0.00	0.00	1.82	0.00	5.45	16.36	69.09	7.27	0.00	55
	SIC-8	0.92	0.00	6.42	1.83	4.59	5.50	2.75	68.81	9.17	109
	SIC-9	0.00	0.89	4.46	3.57	1.79	5.36	1.79	16.07	66.07	112

Table 5: Mobility matrix for men in 9 different industries. For SIC definition see appendix. Cross-section weights applied.

From \ To Industry	SIC-1	SIC-2	SIC-3	SIC-4	SIC-5	SIC-6	SIC-7	SIC-8	SIC-9	*N*
SIC-1	37.50	0.00	0.00	0.00	0.00	0.00	0.00	25.00	37.50	8
SIC-2	0.00	54.55	9.09	18.18	0.00	9.09	0.00	0.00	9.09	11
SIC-3	0.00	5.26	42.11	5.26	0.00	10.53	15.79	0.00	21.05	19
SIC-4	2.56	5.13	7.69	61.54	2.56	7.69	0.00	7.69	5.13	39
SIC-5	0.00	0.00	0.00	14.29	71.43	14.29	0.00	0.00	0.00	7
SIC-6	0.93	0.93	2.78	6.48	0.00	64.81	3.70	7.41	12.04	108
SIC-7	0.00	0.00	6.67	0.00	0.00	6.67	53.33	26.67	6.67	15
SIC-8	1.28	3.85	3.85	2.56	0.00	3.85	2.56	64.10	17.95	78
SIC-9	0.00	0.00	1.72	0.00	0.00	6.90	1.15	4.60	85.63	174

Table 6: Mobility matrix for women in 9 different industries. For SIC definition see appendix. Cross-section weights applied.

Variable	Model I Parameter estimates		Model I Marginal effects	Model II Parameter estimates		Model II Marginal effects
Constant	0.2032	*(0.34)*		0.4203	*(0.65)*	
Age 16-20	0.5410	*(3.29)******	0.1928	0.5425	*(3.11)******	0.1931
Age 21-30	0.2198	*(2.37)****	0.0721	0.2134	*(2.12)****	0.0697
Married	-0.1367	*(1.64)*	-0.0433	-0.1425	*(1.58)*	-0.0451
Children 4-11	0.0913	*(2.09)****	0.0287	0.0995	*(2.10)****	0.0312
Children 12-18	-0.0196	*(0.29)*	-0.0062	-0.0562	*(0.74)*	-0.0176
Job satisfaction	-0.1534	*(6.12)******	-0.0482	-0.1603	*(5.86)******	-0.0502
Training	0.1685	*(2.24)****	0.0540	0.1628	*(2.02)****	0.0520
Log annual income	0.0387	*(0.65)*	0.0121	0.0200	*(0.31)*	0.0063
Job tenure	-0.1410	*(8.85)******	-0.0443	-0.1431	*(7.83)******	-0.0448
Job tenure sq	0.0038	*(6.73)******	0.0012	0.0040	*(5.65)******	0.0013
Unskilled	0.0039	*(0.04)*	0.0012	0.0285	*(0.27)*	0.0090
Firm size < 50	0.1270	*(1.78)**	0.0402	0.1381	*(1.79)**	0.0436
SIC-1	0.1289	*(0.65)*	0.0421	0.0311	*(0.13)*	0.0098
Public	-0.1289	*(1.20)*	-0.0392	-0.1151	*(0.97)*	-0.0351
Scotland	0.1578	*(1.81)**	0.0517	-2.9303	*(2.12)****	-0.3267
London	0.2203	*(1.64)*	0.0731	0.2225	*(1.66)**	0.0737
Unemployment rate	-0.0258	*(0.99)*	-0.0081	-0.0259	*(0.99)*	-0.0081
*Scot*Age 16-20*				0.0825	*(0.21)*	0.0266
*Scot*Age 21-30*				0.1069	*(0.53)*	0.0347
*Scot*Married*				0.0736	*(0.40)*	0.0236
*Scot*Children 4-11*				-0.0769	*(0.84)*	-0.0241
*Scot*Children 12-18*				0.2955	*(1.93)**	0.0926
*Scot*Job satisfaction*				0.0761	*(1.47)*	0.0239
*Scot*Training*				0.0536	*(0.31)*	0.0171
*Scot*Log annual income*				0.2839	*(2.02)****	0.0889
*Scot*Job tenure*				-0.0151	*(0.48)*	-0.0047
*Scot*Job tenure sq*				-0.0001	*(0.12)*	-0.0000
*Scot*Unskilled*				-0.3676	*(1.70)**	-0.0999
*Scot*Firm size < 50*				-0.0651	*(0.41)*	-0.0200
*Scot*SIC-1*				0.5602	*(1.46)*	0.2026
*Scot*Public*				-0.1674	*(0.79)*	-0.0494
N	2228			2228		
Wald χ^2 (d.f.)	193.68 (17)			240.45 (31)		
Prob>χ^2	0.000			0.000		
McFadden's R^2	0.1230			0.1270		
Log likelihood	-1148.11			-1142.09		

Table 7: Probit parameter estimates for English and Scottish males. Dependent variable: job change=1; no change=0. Robust z statistics in parentheses. *significant at 10 per cent **significant at 5 per cent ***significant at 1 per cent. Cross-section weights applied.

Variable	Model I			Model II		
	Parameter estimates		Marginal effects	Parameter estimates		Marginal effects
Constant	1.5866	*(2.56)***		1.7904	*(2.64)****	
Age 16-20	0.3576	*(2.03)***	0.1245	0.3533	*(1.89)**	0.1228
Age 21-30	0.2724	*(2.55)***	0.0911	0.2670	*(2.30)***	0.0892
Married	-0.0512	*(0.56)*	-0.0164	-0.0675	*(0.69)*	-0.0215
Children 4-11	0.0462	*(0.70)*	0.0148	0.0471	*(0.66)*	0.0150
Children 12-18	0.0584	*(0.72)*	0.0186	0.0419	*(0.47)*	0.0134
Job satisfaction	-0.1771	*(5.51)****	-0.0565	-0.1795	*(5.12)****	-0.0572
Training	0.0265	*(0.30)*	0.0085	0.0138	*(0.14)*	0.0044
Log annual income	-0.1025	*(1.71)**	-0.0327	-0.1211	*(1.84)**	-0.0386
Job tenure	-0.1127	*(4.81)****	-0.0360	-0.1068	*(4.22)****	-0.0341
Job tenure sq	0.0023	*(2.36)***	0.0007	0.0021	*(1.98)***	0.0007
Unskilled	-0.0845	*(0.65)*	-0.0264	-0.1069	*(0.75)*	-0.0331
Firm size < 50	-0.0133	*(0.15)*	-0.0042	-0.0296	*(0.32)*	-0.0094
SIC-1	0.2834	*(0.67)*	0.0981	0.2401	*(0.49)*	0.0821
Public	-0.0238	*(0.25)*	-0.0076	-0.0079	*(0.08)*	-0.0025
Scotland	0.1022	*(0.99)*	0.0335	-2.1621	*(1.73)**	-0.3129
London	0.2627	*(1.74)**	0.0889	0.2627	*(1.74)**	0.0888
Unemployment rate	-0.0156	*(0.48)*	-0.0050	-0.0171	*(0.52)*	-0.0055
*Scot*Age 16-20*				0.1135	*(0.28)*	0.0375
*Scot*Age 21-30*				0.0478	*(0.22)*	0.0155
*Scot*Married*				0.1373	*(0.73)*	0.0455
*Scot*Children 4-11*				0.0291	*(0.21)*	0.0093
*Scot*Children 12-18*				0.1240	*(0.71)*	0.0395
*Scot*Job satisfaction*				0.0307	*(0.47)*	0.0098
*Scot*Training*				0.0879	*(0.44)*	0.0288
*Scot*Log annual income*				0.2191	*(1.71)**	0.0699
*Scot*Job tenure*				-0.0751	*(1.51)*	-0.0239
*Scot*Job tenure sq*				0.0029	*(1.50)*	0.0009
*Scot*Unskilled*				0.2199	*(0.81)*	0.0748
*Scot*Firm size < 50*				0.1985	*(1.08)*	0.0669
*Scot*SIC-1*				0.2441	*(0.34)*	0.0837
*Scot*Public*				-0.1049	*(0.53)*	-0.0323
N	1593			1593		
Wald χ^2 (d.f.)	109.97 (17)			145.05 (31)		
Prob>χ^2	0.000			0.000		
McFadden's R^2	0.1040			0.1070		
Log likelihood	-842.34			-840.28		

Table 8: Probit parameter estimates for English and Scottish females. Dependent variable: job change=1; no change=0. Robust z statistics in parentheses. *significant at 10 per cent **significant at 5 per cent ***significant at 1 per cent. Cross-section weights applied

Variable	England	Scotland
Constant	0.2432	-2.6858
	(0.39)	(2.17)**
Age 16-20	0.5400	0.6250
	(3.09)***	(1.81)*
Age 21-30	0.2089	0.3203
	(2.07)**	(1.83)*
Married	-0.1489	-0.0689
	(1.64)	(0.42)
Children 4-11	0.0934	0.0226
	(1.97)**	(0.29)
Children 12-18	-0.0581	0.2393
	(0.77)	(1.80)*
Job satisfaction	-0.1624	-0.0842
	(5.90)***	(1.91)*
Training	0.1613	0.2164
	(2.00)**	(1.41)
Log annual income	0.0288	0.3039
	(0.45)	(2.43)**
Job tenure	-0.1462	-0.1583
	(7.98)***	(6.07)***
Job tenure sq.	0.0041	0.0039
	(5.77)***	(4.77)***
Unskilled	0.0164	-0.3391
	(0.15)	(1.79)*
Firm size < 50	0.1417	0.0731
	(1.84)*	(0.52)
SIC-1	0.0151	0.5912
	(0.07)	(1.93)*
Public	-0.1054	-0.2825
	(0.89)	(1.60)
N	1693	535
Wald χ^2 (d.f.)	168.29 (14)	70.31 (14)
Prob>χ^2	0.000	0.000
McFadden's R^2	0.1230	0.153
Log likelihood	-872.39	-264.54

Table 9: Probit parameter estimates for English and Scottish males. Dependent variable: job change=1; no change=0. Robust z statistics in parentheses. *significant at 10 per cent **significant at 5 per cent ***significant at 1 per cent. Cross-section weights applied

	England	Scotland
Predicted mobility	$\overline{M}_E = 0.28451$	$\overline{M}_S = 0.27243$
Difference in predicted mobility	$\overline{M}_E - \overline{M}_S$	0.01207
Explained (due to differences in *X*s)	ψ	0.03363
Unexplained (due to differences in βs)	φ	-0.02155
Disaggregation of differences into *j* components	*diff Xj*	*diff* βj
Constant		1.31199
Age 16-20	0.00244	-0.00157
Age 21-30	0.00102	-0.01054
Married	0.00114	-0.02191
Children 4-11	0.00000	0.01546
Children 12-18	0.00016	-0.02963
Job satisfaction	-0.00397	-0.17775
Training	0.00398	-0.00596
Log annual income	0.00002	-1.18928
Job tenure	0.07376	0.03558
Job tenure sq	-0.04779	0.01005
Unskilled	0.00005	0.02559
Firm size < 50	0.00079	0.01236
SIC-1	-0.00011	-0.01302
Public	0.00215	0.01706

Table 10: Decomposition of differences in mean predicted mobility rates for males. Cross-section weights applied.

Variable	Males		Females	
	England	Scotland	England	Scotland
No of job changes	0.2815	0.2014	0.2792	0.2281
	(0.5356)	(0.4736)	(0.5422)	(0.4968)
Age 16-20	0.0557	0.0403	0.0731	0.0526
	(0.2295)	(0.1968)	(0.2603)	(0.2235)
Age 21-30	0.2264	0.2102	0.2541	0.2544
	(0.4186)	(0.4078)	(0.4355)	(0.4360)
Married	0.5845	0.6025	0.4765	0.5000
	(0.4930)	(0.4898)	(0.4996)	(0.5005)
Children 4-11	0.4842	0.4781	0.3255	0.3180
	(0.8089)	(0.8213)	(0.6651)	(0.6578)
Children 12-18	0.2123	0.2137	0.2070	0.2259
	(0.5052)	(0.5094)	(0.5164)	(0.5257)
Job satisfaction	5.1610	5.0666	5.2841	5.3333
	(1.3643)	(1.4959)	(1.3659)	(1.3205)
Unskilled	0.1700	0.1646	0.1209	0.1579
	(0.3758)	(0.3712)	(0.3262)	(0.3650)
Log annual income	9.6439	9.6335	9.2801	9.2449
	(0.7130)	(0.6625)	(0.7915)	(0.8410)
Job tenure	4.8972	6.6909	4.0224	4.7934
	(6.1467)	(7.7923)	(4.8966)	(5.5369)
Firm size < 50	0.4279	0.4028	0.4578	0.4956
	(0.4949)	(0.4909)	(0.4984)	(0.5005)
SIC-1	0.0265	0.0490	0.0073	0.0154
	(0.1606)	(0.2161)	(0.0852)	(0.1231)
Public sector	0.1419	0.2084	0.3084	0.3816
	(0.3490)	(0.4065)	(0.4620)	(0.4863)
N	1776	571	1232	456

Table 11: Mean charactersitics for England and Scotland, number of job changes. Cross-section weights applied.

Variable	Males Parameter estimates		Females Parameter estimates	
Constant	-0.0017	(0.00)	0.3696	(0.58)
Age 16-20	0.4560	(2.55)**	0.3471	(1.48)
Age 21-30	0.1219	(0.99)	0.2984	(2.07)**
Married	-0.2137	(1.84)*	-0.1974	(1.53)
Children 4-11	0.1002	(1.80)*	0.0349	(0.40)
Children12-18	-0.2343	(2.32)**	0.1331	(1.14)
Job satisfaction	-0.2050	(7.02)***	-0.1599	(4.14)***
Unskilled	0.0298	(0.24)	-0.1634	(0.87)
Log annual income	0.0300	(0.50)	-0.0470	(0.76)
Job tenure	-0.1945	(7.68)***	-0.1381	(2.96)***
Job tenure sq	0.0045	(6.04)***	0.0021	(0.95)
Firm size < 50	0.2130	(2.24)**	-0.1098	(0.90)
SIC-1	0.0355	(0.12)	0.2902	(0.52)
Public	-0.2746	(1.65)*	-0.2335	(1.58)
Scotland	-2.8033	(1.70)*	-0.8885	(0.66)
Unemployment rate	-0.0121	(0.42)	-0.0024	(0.07)
Scot Age 16-20*	-0.2699	(0.53)	0.1955	(0.40)
Scot Age 16-20*	0.3379	(1.28)	0.0729	(0.25)
*Scot*Married*	0.2223	(0.89)	0.1788	(0.67)
Scot Children 4-11*	-0.1505	(1.08)	-0.1995	(1.08)
Scot Children 12-18*	0.4698	(2.58)***	0.0509	(0.22)
*Scot*Job satisfaction*	0.0597	(0.67)	-0.0261	(0.28)
Scot Unskilled*	-0.6765	(2.06)**	-0.0402	(0.11)
Scot Log annual income*	0.2436	(1.52)	0.1138	(0.89)
Scot Job tenure*	-0.0456	(0.82)	-0.1588	(1.77)*
Scot Job tenure sq*	0.0006	(0.46)	0.0070	(1.96)*
Scot Firm size < 50*	0.0801	(0.33)	0.1441	(0.58)
*Scot*SIC-1*	0.2871	(0.61)	0.4049	(0.52)
*Scot*Public*	-0.0836	(0.25)	0.0357	(0.12)
N	2347		1688	
Wald χ^2 *(d.f.)*	251.81 (28)		130.20 (28)	
Prob>χ^2	0.0000		0.0000	
Log likelihood	-1643.04		-1043.94	

Table 12: Parameter estimates from a zero inflated Poisson model for males and females, respectively. Logit results are not reported. Dependent variable: number of job changes. Robust z statistics in parantheses. *significant at 10 per cent **significant at 5 per cent ***significant at 1 per cent. Cross-section weights applied.

Variable	Males Parameter estimates	
Constant	-0.0329	(0.05)
Age 16-20	0.4578	(2.56)**
Age 21-30	0.1237	(1.00)
Married	-0.2132	(1.83)*
Children 4-11	0.1003	(1.80)*
Children12-18	-0.2338	(2.32)**
Job satisfaction	-0.2027	(6.92)***
Unskilled	0.0311	(0.25)
Log annual income	0.0317	(0.53)
Job tenure	-0.1945	(7.68)***
Job tenure sq	0.0045	(6.04)***
Firm size < 50	0.2136	(2.24)**
SIC-1	0.0355	(0.12)
Public	-0.2741	(1.65)*
Scotland	-2.7485	(1.67)*
Unemployment rate	-0.0117	(0.40)
Scot Age 16-20*	-0.2736	(0.54)
Scot Age 16-20*	0.3355	(1.27)
*Scot*Married*	0.2214	(0.89)
Scot Children 4-11*	-0.1505	(1.08)
Scot Children 12-18*	0.4688	(2.57)**
*Scot*Job satisfaction*	0.0555	(0.63)
Scot Unskilled*	-0.6798	(2.07)**
Scot Log annual income*	0.2403	(1.50)
Scot Job tenure*	-0.0458	(0.83)
Scot Job tenure sq*	0.0006	(0.47)
Scot Firm size < 50*	0.0795	(0.33)
*Scot*SIC-1*	0.2867	(0.61)
*Scot*Public*	-0.0834	(0.25)
N	2347	
Wald χ^2 (d.f.)	249.91 (28)	
Prob>χ^2	0.0000	
Log likelihood	-1643.04	

Table 13: Parameter estimates from a Poisson model for males. Dependent variable: number of job changes. Robust z statistics in parantheses. *significant at 10 per cent **significant at 5 per cent ***significant at 1 per cent. Cross-section weights applied.

A Data definition

The depend variable for the overall job mobility captures all job changes including promotions, layoffs and quits, based on the question whether the current job has been acquired before or after the last interview 12 months ago. The endogenous variable for the zero inflated Poisson model is derived from the question on the number of separate jobs held in the reference year, including different jobs with the same employer and self-employment spells. Employment is defined by whether the respondent did paid work in the previous week, or did no paid work in that week but has a job and was away from it. The exogenous variables are taken from wave nine only, their definition is as follows:

Age 16-20	(0,1) dummy indicating whether individual falls in age group 16 to 20
Age 21-30	(0,1) dummy indicating whether individual falls in age group 21 to 30
Married	(0,1) dummy indicating whether individual is married
Children 4-11	number of children aged 4 to 11
Children 12-18	number of children aged 12 to 18
Job satisfaction	asks respondent to state overall work satisfaction on a scale 1 to 7, where 7 is completely satisfied
Training	asks whether respondent has taken any part-time courses in the last 12 months
Log annual income	log annual labour income in the last 12 months
Job tenure	years spend in the current job
Unskilled	current job is in unskilled occupation
No higher education	respondent has no higher education such as higher degree, a-level or o-level
Firm size<50	respondent works in firm that has less than 50 employees
Public sector	respondent works in the public sector, where public sector includes civil service, central and local government, nationalised industry and NHS

Originally, a wider range of covariates had been considered, including further education variables (higher degree, a-level, o-level), further occupational groups (professional, managerial, skilled manual, skilled non-manual), travelling time to work, firm size >50 as well as dummies on overtime, unionism, ethnicity and specific training. However, all of these variables were insignificant or reduced the sample size significantly, such as unionism, and have been left out of the final model. The analyses have been carried out using STATA 7.0 framework.

B Industry codes

Standardised industry classification (SIC), 1980:

SIC-1	Energy and water supply
SIC-2	Extraction of minerals and ores other than fuels; manufacturing of metals, mineral products and chemicals
SIC-3	Metal goods, engineering and vehicles industries
SIC-4	Other manufacturing industries
SIC-5	Construction
SIC-6	Distribution, hotels and catering (repairs)
SIC-7	Transport and communication
SIC-8	Banking, finance, insurance, business services and leasing
SIC-9	Other services