Job Mobility in Ireland

Adele Bergin*

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Abstract

This paper investigates the factors that determine job-to-job mobility in Ireland over the period 1995 to 2001. It finds that labour market experience, working in the public sector, human capital, whether a person is overskilled and the sector they work in are important determinants of job change. In addition, the paper finds the rate of job mobility in Ireland practically doubled over the period. The sample is divided into two time periods and a decomposition technique is applied to ascertain how much of the increase in mobility is attributable to compositional changes and how much is due to other factors.

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* The Economic and Social Research Institute, Whitaker Square, Sir John Rogerson's Quay, Dublin 2, Ireland and Economics, Finance and Accounting Department NUI Maynooth.
Email: adele.bergin@esri.ie
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1. Introduction

The focus of this paper is to investigate the various factors that determine job-to-job mobility in Ireland. Job mobility is an important phenomenon to understand because the movement of workers from one job to another allows for flexibility in the labour market by providing workers and firms with a mechanism to adapt to changing economic and personal circumstances. It is a process that allows for and promotes allocative efficiency in the labour market.

One of the findings of the paper is that the rate of job mobility doubled over the period 1995 to 2001. The paper investigates the potential causes of this increase. During this period, there was a dramatic expansion in the labour force so the increase in job mobility may simply be driven by changes in the composition of workers. However, other factors such as changes in the labour market conditions facing workers may also play a role.

This paper is organised as follows: Section 2 surveys the theoretical literature on job mobility and outlines what the literature tells us we should observe in the data, Section 3 describes the dataset, the construction of key variables and provides some descriptive statistics. Section 4 presents the results of probit models of job change and how we take account of changes in the labour market environment over time. Section 5 outlines a decomposition technique that is used to ascertain the extent to which the increase in the mobility rate is driven by changes in the composition of the sample. Section 6 concludes.

2. Background

2.1 Why do Workers Change Jobs? Theoretical Models

A multitude of theoretical models exist that explain why we observe job mobility and the subsequent effect of mobility on wages. In these models the labour market is typically characterised by imperfect information or by some degree of heterogeneity. It is usually assumed that there is a range of different jobs in the labour market and that individual workers differ in their ability to perform the tasks associated with any of these jobs. In other models, the assumption of imperfect information means that firms are uncertain about the productivity of a worker at the beginning of an employment relationship. As a result, workers may not be initially employed in the jobs in which they are the most productive. Job mobility provides a mechanism for the labour market to move towards a more efficient allocation of resources whereby workers sort themselves into jobs that maximise their productivity. Three main theoretical approaches can be distinguished from the literature, namely job search models, job matching models and human capital models.

At the core of job matching models is the idea that the labour market is characterised by imperfect information. In Jovanovic's (1979) seminal contribution, the quality of an employment match, where quality is defined in terms of the worker's actual productivity in a particular job, is not known *ex ante*. Employees learn through experience how suited they are to a job and as tenure on the job increases, information about the worker's productivity is revealed and prior expectations about the quality of the match are updated. This information leads to either job continuance or job turnover when the quality of the match is worse than initially expected. Consequently the probability of mobility declines with tenure. Workers move to increasingly higher quality matches, where they are rewarded more for their particular aptitudes. This model predicts a positive relationship between job mobility and wages, although it is not a direct relationship but rather wages are affected through improved match quality.

In job search models, there is heterogeneity across workers in their ability to perform certain jobs. For example, in Burdett's job search model (1978), the quality of the match is known *ex ante* so workers face a distribution of productivity and wages that reflect their ability to perform different jobs. Workers can continue to search for a better job after accepting a job offer. Another firm will offer the individual a wage that reflects the person's productivity in that particular firm. The more intensely a worker searches, the faster is the arrival rate of alternative offers. The worker will accept any offer received with a wage higher than their current wage after allowing for any costs involved in changing jobs. In this type of model, as workers gain more labour market experience they have more opportunities to search for, evaluate and accept superior job offers. Consequently, as experience increases so does the worker's reservation wage for changing jobs so the probability of job mobility declines with experience.

Human capital models (such as Becker (1962) and Oi (1962)) imply an inverse relationship between job mobility and investment in job-specific skills, which incorporates both on-the-job experience and any formal training. As tenure in a job increases, workers acquire more specific human capital and this creates a higher earnings potential for that person in their job, and so reduces the probability of job mobility. The nature of the human capital a worker acquires on-the-job, in particular its transferability to another job, will determine the wage impact of changing jobs. If firm-specific skills are an important determinant of earnings, changing jobs may result in wage losses.

Many modern theoretical models build on the models described above. However there are alternative approaches. Blumen et al. (1955) was one of the first models of job mobility. In their mover-stayers model, workers have an unobservable characteristic such as the capacity to stay in a job, that affects their productivity. High productivity workers will avoid job turnover, while low productivity workers will change jobs frequently. In this model, mobility is negatively correlated with wages because it is correlated with the unobservable characteristic that determines mobility. In direct contrast, in Lazear's (1986) raiding model, mobility acts as a positive signal of productivity and leads to wage gains. In this model, firms use workers previous wages as an indicator of their quality and so high productivity workers experience more mobility than low productivity workers because the highest paying firms poach workers from their rivals.

2.2 Patterns we should observe in the Data

Effects of Tenure, Age and Experience

Age is an important factor determining job mobility and turnover declines with age. In Stigler (1962) younger workers are more likely to try a variety of jobs in order to acquire knowledge of the labour market and their own preferences and ability for different jobs (a process known as "job shopping") so we should expect to see higher mobility rates for younger workers. As workers gain labour market experience, they move to better job matches. In job search models, with each job change the worker moves up the wage offer distribution leaving them with fewer jobs to which it would be worthwhile for them to move to in the future so mobility declines with experience. This is supported empirically by numerous studies. For example, Topel and Ward (1992) find that for young men two thirds of their total lifetime job mobility occurs within the first ten years of their career. They see job mobility for young workers as a crucial phase in workers' movement to more long-term stable employment relationships.

The probability of job mobility also declines with tenure. In job matching models, when the quality of the match is revealed, workers in a successful match may be rewarded with higher wages or match specific rents. If tenure indicates the existence of a successful match then these rents may reduce job mobility for workers with longer tenures. In human capital models, workers accumulate firm-specific human capital over time that they will not be rewarded for in a different firm so as tenure in a job increases the probability of turnover is reduced.

In addition, Groot and Verberne (1997) argue that mobility is likely to be higher for younger people or for those with less labour market experience or less tenure due to the presence of mobility costs. There are both financial and psychological costs to changing jobs. Older people are more likely to have made investments in housing and be more settled or attached to their environment. The costs of changing jobs are likely to be higher for older people, especially if changing jobs involves moving house. Workers with longer tenure are likely to have higher psychological costs in changing jobs. To the extent that longer tenure reflects high quality matches, these workers may feel a stronger attachment to their organisation and colleagues. In addition, even if the costs associated with changing jobs are the same for younger and older people, younger people have more time before retirement to make up these costs. Finally, workers change jobs if the expected utility from doing so exceed the costs. If the gains involved in changing jobs put a worker on a higher wage path younger workers will benefit for longer from these gains. In addition, older workers may have higher time preferences and therefore apply a higher discount rate on future earnings so job mobility declines with age.

Gender

Central to why we might expect differential mobility rates by gender is that women have a lower attachment to the labour force. Barron et al. (1993) develop a job-matching model where workers differ in their attachment to the labour force. The model predicts that those with a weaker attachment to the labour force are sorted into jobs that offer less training and that use less capital and as a result have less to lose by changing jobs in terms of specific capital. On the other hand, women may be less likely to change jobs if they are more constrained by nonmarket variables such as their partner's location or the rearing of children (Royalty, 1993). Empirically, several studies have found that by controlling for characteristics, such as labour market experience, gender differences in turnover rates diminish or disappear (e.g. Blau and Kahn, 1981; Loprest, 1992; Booth and Francesconi, 1999).

Education

There are several reasons to expect a relationship between education and job mobility but there is no consensus in the literature as to whether it is positive or negative. On the one hand the specific human capital model implies that education increases job duration and therefore reduces mobility. It is also possible that individuals with more firm-specific human capital may be less likely to experience job change because the specific nature of their human capital may have no value to other employers. Connolly and Gottschalk (2006) observe that less educated workers may invest less in human capital and consequently have less to lose by changing jobs. They will therefore have a lower reservation value when approached with an alternative job offer. Weiss (1984) suggests that there is an unobservable characteristic, which he calls “stick-to-itiveness”, that affects both the value of education and the value of staying in an existing job. In addition, Barron et al. (1993) argue that education may qualify workers for high training jobs or capital-intensive jobs and so incentives are offered to decrease the expected number of quits for better-educated workers. Neal (1999) proposes a model of job search that involves both employment matches and career matches. He argues that less educated workers are likely to experience more job turnover because they experience mobility that involves career change and then they search for a good employment match. Therefore, it is possible that the process of finding a good career match may add considerably to the wage growth of younger workers, especially the less educated. To the extent that better educated workers (especially those with college degrees) use time spent in education as a form of pre-market search, they are less likely to experience mobility that involves career changes.

However, it is also possible that there could be a positive relationship between education and mobility. Weiss (1984) argues that education increases workers alternative opportunities and so may increase job mobility. Johnson (1979) argues that higher wage variance may increase the option value of job mobility so highly educated workers may experience more job turnover as they face more variable but potentially more rewarding alternative job offers. In addition, Greenwood (1975) contends that highly educated individuals may be more efficient job searchers and so have lower transactions costs and therefore may change jobs more easily. It is possible that better educated workers are more likely to have ‘faster’ careers and will change jobs more frequently as a means of advancing up the career ladder (Borsch-Supan, 1987). Finally, Bartel and Lichtenberg (1987) put forward the idea that highly educated workers have a comparative advantage in learning and implementing new technologies and so firms may provide incentives to reduce job quits.

3. Dataset, Defining Job Mobility and Descriptive Statistics

3.1 Dataset and Sample Construction

The Living in Ireland Survey (LIS) is used to investigate the determinants of job change. The LIS constitutes the Irish component of the European Community Household Panel (ECHP) which began in 1994 and ended in 2001. It involved an annual survey of a representative sample of private households and individuals aged 16 years and over in each EU member state, based on a standardised questionnaire. A wide range of information on variables such as labour force status, occupation, income and education level is collected. There is also a wealth of data collected on job and firm characteristics.[1]

To identify those who have changed jobs I make use of the panel dimension of the LIS. A revolving balanced panel of people aged 20 to 60 has been selected from the

[1] There was some attrition in the sample in the earlier years, although the representativeness of the sample was improved in 2000 with the addition of new households. These new entrants to the LIS sample have been excluded from the analysis.

LIS. The reason for this is that a balanced panel prevents the entry of younger people into the sample and so over time as the fixed sample ages the proportion of younger people would decline.[2] The rule for selection into the sample is that an individual must have been interviewed in each wave when they are between the ages of 20 and 60, roughly the prime working age.[3] Each individuals labour force status is then categorised on a PES basis. I only consider cases where labour force status is available in each year they are eligible for inclusion in the sample. In each year there are around 20 people whose labour force status cannot be classified.[4] These cases are deleted from each year of the sample.

Table 1 shows the total sample size each year and provides some basic characteristics of the sample. The average age of the sample declines over the period implying that the impact of the baby boom generation outweighs the effect of the ageing of the sample. The sample participation rate appears high but it is measured as the proportion of people in the labour force aged 20 to 60 as a percentage of the total number of people age 20 to 60.[5] The male participation rate is significantly above that of the female participation rate, however there is a dramatic rise in the female rate over the period. The table also shows that participation rates decline with age, as we would expect, and that the participation rates for those over the age of 30 increased between 1994 and 2001.[6]

Table 1: Revolving Balanced Panel of Individuals aged 20 to 60

	1995	1996	1997	1998	1999	2000	2001
Total Sample Size	2,417	2,367	2,338	2,299	2,294	2,325	2,357
Average Age	42.0	41.8	41.5	41.2	40.9	40.4	40.1
Participation Rate	64%	65%	68%	70%	72%	72%	73%
Participation Rate: Male	90%	89%	90%	90%	91%	90%	90%
Participation Rate: Female	40%	43%	47%	51%	54%	56%	57%
Participation Rate: 20-29	79%	81%	81%	81%	83%	78%	80%
Participation Rate: 30-39	70%	72%	74%	77%	76%	79%	78%
Participation Rate: 40-49	66%	67%	71%	73%	76%	76%	75%
Participation Rate: 50-60	48%	49%	51%	54%	55%	59%	61%

[2] For example, someone who is 20 in 1995 will be 26 in 2001 and if we only considered the same group of people over time (a balanced panel), there would be no one below the age of 26 in the panel by 2001. Effectively, a revolving balanced panel allows younger people into the sample in later years.
[3] This approach to selecting a sample is similar to that of Baker and Solon (1999).
[4] These individuals are either not working and no reason is given for why they are not seeking work or in the bulk of cases they are in remedial training or sheltered workshops.
[5] Using CSO data, the participation rate for those aged 15 to 64 rose from 60 to 66 per cent over the period. This is below the participation rate of the sample given in Table 2, but it considers more younger and older people who are less likely to be in the labour force and so it is at least consistent with the rate given in Table 2.
[6] There is a 5-percentage point drop in the participation rate for people aged 20 to 29 between 1999 and 2000. This is explained by an increase in the proportion of younger people staying on in education, in particular those aged 20.

3.2 Calculation of Job Mobility

The LIS does not contain an explicit question about changing jobs. However, job mobility can be inferred from answers to the question '*When did you begin work with your present employer (or in your present business)? Please specify the month and the year*'. The response to this question is used to measure workers tenure in their current job. If we observe that an individual was working in the previous year and if their response to this question in the current year is less then the time elapsed between interviews then we conclude that this person has changed jobs.

Job mobility is defined in terms of employment-to-employment transitions. To capture this in the data workers need to be employed in two consecutive years. For example, someone who is employed in one year and then unemployed for two years and then employed again is not included in the analysis. Even though this person has changed jobs over the four-year period, they have moved from being employed to being unemployed for two years to being employed again. Restricting the sample to people who are employed in consecutive two-year periods means that this type of case is excluded. I have excluded these types of transitions because the decision to change jobs is different to the decision to move from, say nonparticipation or unemployment to employment. This definition of job mobility only allows people to be unemployed or to not participate in the labour market for a relatively short amount of time between jobs, essentially less then a year (or more precisely less then the amount of time between interviews). In addition, this measure of job mobility may underestimate total job mobility if more then one job change occurs between subsequent interviews. Farber (1999) states that one of the central facts about job mobility is that there is a high hazard of jobs ending within the first year of an employment relationship.

Individuals' who are employed in successive two-year periods are selected from the revolving balanced panel.[7] The resulting sample is one with workers who have a high attachment to the labour force. In each year around 12 people do not give a response to the question about how long they have been with their current employer and they are excluded from the sample. This results in 1,916 people in the analysis and 9,377 person-year observations. Table 2 shows the number of workers employed in consecutive two-year periods and the rate of job change. Each year approximately 10 per cent of workers change jobs. However, this figure masks an important trend evident in the data. In 1995, 6.5 per cent of workers changed jobs and this rate increased over the period so that by 2000 the mobility rate was 13.5 per cent.

Table 2: Job Mobility Rate

	1995	1996	1997	1998	1999	2000	2001
Number of workers	1,185	1,229	1,274	1,337	1,406	1,449	1,497
No. Job Changes	77	89	110	146	151	195	159
Job Mobility Rate	6.5%	7.2%	8.6%	10.9%	10.7%	13.5%	10.6%

[7] These are all people who work or who usually work at least 15 hours per week.

A total of 927 job changes are identified, however, some people changed jobs more than once so Table 3 shows the number of jobs held by the 1,916 workers between the beginning and end of the 7-year period.

Table 3: Number of Job Changes per Worker

0	1,328
1	375
2	126
3	57
4	21
5	9

To put Ireland in an international context, Table 4 shows average estimates of job mobility for young workers over the period 1995 to 2001 across a range of European countries. From the Table we can see that young workers in Ireland have a relatively high rate of job mobility.

Table 4: Job Mobility Rates, Average between 1995-2001 for workers under 30 in 1994

Germany	6%
Netherlands	8%
Austria	8%
Portugal	9%
Belgium	10%
France	10%
Italy	10%
Greece	13%
Ireland	16%
UK	19%
Finland	22%
Spain	23%

Source: Davia (2005), estimates derived from the European Community Household Panel Survey.

The LIS also asks the main reason for the previous employment relationship ending. This allows us to identify worker initiated or voluntary quits such as obtaining a better job, family-related quits etc and employer related or involuntary quits such as redundancy, dismissal, business closure etc. It may be important to be able to distinguish between voluntary and involuntary job turnover as the reason for job separation is likely to have different impacts on subsequent wage growth.[8] Table 5 gives the main reason why job changers stopped working in their previous jobs. In each year the bulk of job changes were voluntary, with 50 per cent of job changes

[8] For example, Keith and McWilliams (1999) find differential rates of return to job mobility in the US depending on whether the reason for separation is voluntary or involuntary.

being voluntary in 1995 rising to just around 65 per cent in 2001.[9] In 1995 32 per cent of mobility was involuntary and this tended to fall over the period so that by 2001 around 21 per cent of job changes were involuntary. Unfortunately, around 16 per cent of people who changed jobs over the period did so for another other reason that wasn't included in the questionnaire or they did not answer the question. In the analysis that follows, all types of job changes are considered together. Otherwise, we would have to either arbitrarily assign or exclude the workers who do not provide a reason for changing jobs. In addition, the distinction between voluntary and involuntary quits is not totally clear-cut. For example, an employee who stops working in their previous job because they became ill is counted as a voluntary changer.

Table 5: Reason for Stopping Previous Job

	1995	1996	1997	1998	1999	2000	2001
Voluntary Turnover:							
Got Better Job	47%	43%	43%	42%	46%	54%	57%
Other Reasons Given	3%	7%	10%	15%	16%	12%	9%
Involuntary Turnover:							
Obliged to Stop	10%	11%	12%	16%	8%	10%	9%
End of Contract	22%	24%	15%	11%	15%	11%	12%
Rest	18%	16%	20%	15%	15%	12%	13%

3.3. Descriptive Statistics

This section examines some individual characteristics of workers and of those who change jobs. The aims are to identify differences in characteristics between those who change jobs and those who stay in their jobs and also to identify any compositional changes in the total number of workers that might help explain the rise in the rate of job change.

Age

The age distribution of all workers in the sample (from Table 2) is given in Table 6. The proportion of workers in the 20 to 29 age group increases over time, and the increase is more marked in 2000 and 2001, reflecting the fact that these younger people only have to be working for a relatively short period of time for them to be included in the sample. The proportion of workers in the 30-39 age group declines over the period, consistent with the ageing of the sample over time. The proportion of the workers in the 40 to 49 age group increases up to 2000, again indicating the ageing of the sample.[10] The proportion of workers between 50 and 60 declines

[9] Included in the 'Other Reasons Given' category in Table 5 are explanations such as childbirth or looking after children, looking after an old, sick or disabled person, that their partner's job required them to move to another place, study, or that the person became ill or disabled.

[10] The proportion declines slightly from 2000 to 2001. The numbers leaving to enter the older age group roughly cancels out the number of people entering this age group and because the number of

slightly over the period because the impact of people dropping out of the sample at 60 slightly dominates the effect of ageing. There is a slight decrease in the average age of workers over the period due to the impact of the 'baby boom' generation.

Table 6: Age Distribution of Sample

	1995	1996	1997	1998	1999	2000	2001
20-29	18%	19%	21%	22%	23%	25%	25%
30-39	30%	30%	28%	27%	25%	24%	23%
40-49	26%	27%	28%	28%	29%	29%	28%
50-60	26%	24%	23%	23%	23%	23%	24%
Average Age	40.9	40.5	39.9	39.8	39.7	39.4	39.7

Table 7 shows the percentage of each age group who change jobs over time. From the table we can see that the propensity to change jobs declines with age and this finding is consistent with the empirical literature. The increasing proportion of young people aged 20 to 29 is at least in part driving the increase in the overall mobility rate. Interestingly, the mobility rates for workers over the age of 30, although somewhat volatile over the period, show quite large increases. For example, the rate of job change for those between 30 and 39 almost trebles over the period, albeit from a much lower base then comparable rates for workers aged between 20 and 29. From Tables 6 and 7 we can see that workers who change jobs are on average 6/7 years younger then the sample average.

Table 7: Job Change Rate by Age Group

	1995	1996	1997	1998	1999	2000	2001
20-29	19%	18%	23%	22%	22%	27%	19%
30-39	4%	6%	5%	10%	10%	13%	11%
40-49	5%	5%	5%	6%	8%	6%	7%
50-60	2%	3%	4%	7%	4%	8%	6%
Average Age of Job Changers	32.8	33.5	32.5	34.6	32.9	33.3	34.7

Gender

Table 8 shows the gender distribution of workers over time. Female workers account for a rising proportion of workers over time capturing female workers who returned to the labour market. The percentage of men and women who change jobs is given in Table 9. Both the male and female rates of job mobility double over the period 1995 to 2000. The female job change rate is around 1.5 percentage points above the male rate so the changing gender distribution of workers may be contributing somewhat to the rise in the overall job mobility rate over the period.

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people in the younger age group is increasing quite dramatically the share of the total accounted for by the 40 to 49 age group declines somewhat.

Table 8: Gender Distribution of Workers

	1995	1996	1997	1998	1999	2000	2001
Male	69%	67%	66%	63%	63%	63%	61%
Female	31%	33%	34%	37%	37%	37%	39%

Table 9: Job Change Rate by Gender

	1995	1996	1997	1998	1999	2000	2001
Male	6%	6%	9%	10%	11%	12%	11%
Female	7%	9%	8%	13%	11%	15%	11%

Education

Table 10 shows the education distribution of all workers where low-skilled workers are those who have at most Junior Certificate education, medium-skilled are those who have at most a diploma and high-skilled are those with degrees.[11] From the table, an improvement in the educational attainment of workers is apparent with low-skilled workers accounting for a declining proportion of total workers and medium- and high-skilled workers accounting for an increasing proportion over time.

Table 10: Education Distribution of Workers

	1995	1996	1997	1998	1999	2000	2001
Low-Skilled	49%	48%	48%	41%	39%	36%	34%
Medium-Skilled	37%	39%	39%	44%	45%	47%	49%
High-Skilled	14%	13%	13%	15%	16%	16%	17%

Table 11 shows the percentage of workers within various education groups who have changed jobs. The table shows that medium-skilled workers have a slightly higher propensity to change jobs than low-skilled workers, while high-skilled workers have the lowest rate of job change. The rise in the proportion of medium-skilled workers may be contributing a small amount to the rise in overall mobility rates.

Table 11: Job Change Rate by Education Level

	1995	1996	1997	1998	1999	2000	2001
Low-Skilled	6%	7%	10%	11%	10%	12%	12%
Medium-Skilled	7%	9%	10%	12%	12%	14%	11%
High-Skilled	7%	3%	2%	7%	8%	14%	7%

Occupation

The occupations workers have may provide a measure of more specific human capital or skills, while education level is probably a better indicator of more general human

[11] There are between 1 and 7 cases each year where the answer to the educational attainment question is missing. For these people, their educational attainment is assigned to them on the basis of the age at which they left full time education.

capital. The occupational distribution of workers is given in Table 12 and Table 13 shows the propensity for workers in different occupations to change jobs.[12] As job changes may involve occupational change the data in the Tables refer to the occupation held in the previous year. Table 12 shows that over the period there is generally some decline in the proportion of workers who are managers, professionals and skilled workers, while the proportion of workers in elementary occupations and clerks increases over the period. Table 13 shows much more variability in the rates of job mobility by occupation than by education level. Clerks and those in elementary occupations have roughly double the rate of job change of managers, professionals and skilled workers. Around half of the job changes identified involve a change in occupation.

Table 12: Occupational Distribution of Workers

	1995	1996	1997	1998	1999	2000	2001
Manager	12%	11%	10%	9%	8%	8%	10%
Professional	25%	25%	26%	24%	25%	24%	24%
Skilled	23%	23%	22%	21%	20%	21%	21%
Clerk	21%	22%	22%	23%	24%	26%	26%
Elementary Occupations	18%	19%	20%	22%	22%	22%	19%

Table 13: Job Change Rate by Occupation

	1995	1996	1997	1998	1999	2000	2001
Manager	6%	6%	3%	4%	7%	6%	8%
Professional	4%	5%	5%	6%	7%	10%	6%
Skilled	6%	5%	7%	6%	8%	10%	11%
Clerk	9%	10%	10%	15%	11%	18%	14%
Elementary Occupations	8%	11%	16%	19%	19%	18%	12%

Sector

The share of workers in each sector is given in Table 14. The average shares over the period are broadly comparable to the employment shares from the Labour Force Survey and Quarterly National Household Survey, with the exception of the share employed in agriculture which exceeds the CSO data by around 5 percentage points and the share in market services which is around 5 percentage points lower then the

[12] In the LIS, occupations are classified according to the International Standard Classification of Occupations, version 1988 (COM) 1-digit codes. In Tables 11 and 12 the ‘Manager’ category comprises managers, senior officials and legislators; the ‘Professional’ category includes those working in the armed forces, professionals, technicians and associated professionals; the ‘Clerks’ category includes clerks, and service, shop and sale workers; the ‘Skilled’ category comprises skilled agricultural or fishery workers and skilled craft or trade workers and finally the ‘Elementary Occupations’ category includes those in elementary occupations and plant or machine operators and assemblers.

CSO data.[13] The declining importance of agriculture in terms of its share in employment and the rising importance of market services are evident. As with occupations, a job change may involve changing sector so the data in the Tables 14 and 15 refer to the sectors workers were in the previous year.

Table 14: Sectoral Distribution of Workers

	1995	1996	1997	1998	1999	2000	2001
Agriculture & Mining	15%	14%	12%	12%	11%	10%	9%
Manufacturing	18%	18%	19%	21%	19%	19%	19%
Utilities	1%	1%	1%	1%	1%	1%	1%
Construction	7%	8%	7%	7%	8%	8%	9%
Market Services	33%	32%	35%	34%	36%	36%	38%
Non Market Services	25%	26%	26%	26%	24%	25%	24%

There is considerable variability in job mobility by sector (see Table 15). Workers in construction and market services display the highest rate of job turnover, while those in non-market services (predominately public sector workers), and those in the agricultural sector are least likely to change jobs.

Table 15: Job Change Rate by Sector

	1995	1996	1997	1998	1999	2000	2001
Agriculture & Mining	1%	4%	4%	6%	6%	7%	3%
Manufacturing	4%	5%	9%	11%	9%	10%	10%
Utilities	0%	0%	0%	0%	7%	0%	0%
Construction	19%	18%	20%	8%	19%	24%	20%
Market Services	11%	11%	11%	16%	14%	18%	14%
Non Market Services	3%	3%	4%	8%	7%	9%	5%

From the preceding analysis age, occupation and sector appear to be important in explaining job change. The following section explores the factors that determine job change more formally. The increase in job mobility over the 1995 to 2001 period does not appear to have been driven by changes in the composition of the sample, although the increase in the proportion of younger people and changes in occupational and sectoral distributions of workers may account for part of it. The rise in job mobility may be related to the rapid output and employment growth observed over the period and we try to capture this effect in the next section. Section 5 examines the extent to which the rise in mobility is driven by compositional changes in the sample.

[13] The market services sector comprises distribution, hotels and restaurants, transport, storage and communications, financial intermediation, real estate, renting and business activities and other services; the non-market services sector includes public administration and defence, education, health and social work.

4. Probit Model of Job Change

Table 16 reports the marginal effects of a probit regression explaining job change, where the dependent variable is equal to one if the person has changed jobs and zero otherwise. The data for 1995 to 2001 have been pooled so that there are 9,377 observations from which I have identified 927 job changes. The explanatory variables are defined in Appendix Table 1. The marginal effects are computed at the means of the explanatory variables.

Beginning with the first model presented in the Table (Specification 1) the signs and significance of the coefficients are, in general, what would be expected. The marginal effect of experience is negative and highly significant implying that for a worker with mean characteristics an additional year of experience is associated with a 0.9 percentage point decrease in the probability of changing jobs. Experience may have a non-linear effect on the probability of changing jobs so to capture the fact that job changes are more likely to occur early in one's career a squared term is included in the specification. The positive effect on the experience-squared variable implies that the greater years of experience is the bigger the (negative) effect experience has on the probability of job change.

The marginal effect on gender is small and insignificant implying that there are not gender differences in the probability of changing jobs. Looking at household structure, workers who are married are less likely to change jobs but the effect is not significant. If people are constrained by their partners' job we might expect the effect to be bigger for women. A gender and marital status interaction term is included and the effect is significant at the 10 per cent level. The marginal effect on the children variable is small and insignificant implying that having children does not affect the probability of changing jobs.[14] This is somewhat surprising but may partly be explained by the fact that the sample considers people who have a high attachment to the labour force.

The education variables capture general human capital and the marginal effects are negative implying that workers with more academic qualifications are less likely to change jobs, although the marginal effect on degree level education is only significant at the 10 per cent level. The negative effects on the occupations of origin imply that people in occupations that embody more human capital than the base category (elementary occupations) are less likely to change jobs. The model results also show that workers in the public sector have a lower probability of changing jobs. Overall, human capital (both general and more specific human capital) reduces the probability of job change.

Workers who report that they are overskilled, meaning they report they have skills and qualifications necessary to do a more demanding job, have a higher probability of changing jobs. This is not surprising given that overskilling may indicate a poor job match. In addition, there is a firm size effect with workers in firms with more then 50 employees less likely to change jobs possibly because they have more alternative opportunities within the firm. Regional dummies and urban/rural dummies were also included but were dropped from the final specification. These location variables were

[14] Alternative formulations of this variable such as including the number of children were examined. A gender and children interaction was included but was dropped because it was not significant.

included to try to capture the extent to which say proximity to a city means a worker has more alternative employment opportunities.

Table 16: Probit Model of Job Change

Variable	*Marginal Impact*	*P>|z|*	*Marginal Impact*	*P>|z|*
	Specification 1		*Specification 2*	
Experience	-0.0086	0.00	-0.0087	0.00
Experience squared	0.0001	0.00	0.0001	0.00
Education- medium	-0.0164	0.01	-0.0163	0.01
Education- high	-0.0188	0.06	-0.0186	0.06
(Ref: Education – low)				
Female	0.0007	0.94	0.0008	0.92
Children	0.0036	0.62	0.0040	0.59
Married	-0.0117	0.24	-0.0116	0.24
Female*Married	-0.0197	0.07	-0.0199	0.06
Public Sector	-0.0287	0.00	-0.0289	0.00
Number of Employees > 50	-0.0236	0.00	-0.0240	0.00
Overskilled	0.0287	0.00	0.0289	0.00
Occupation of Origin:				
(Ref: Elementary Occ's)				
Manager	-0.0510	0.00	-0.0519	0.00
Professional	-0.0456	0.00	-0.0461	0.00
Clerk	-0.0341	0.00	-0.0345	0.00
Skilled	-0.0428	0.00	-0.0435	0.00
Sector of Origin:				
(Ref: Non Market Services)				
Agriculture & Mining	-0.0419	0.00	-0.0420	0.00
Manufacturing	-0.0294	0.01	-0.0295	0.01
Utilities	-0.0648	0.04	-0.0652	0.04
Building	0.0566	0.00	0.0557	0.00
Market Services	0.0182	0.06	0.0177	0.07
Year Dummies:				
(Ref: 1995)				
1996	0.0028	0.81		
1997	0.0114	0.34		
1998	0.0386	0.00		
1999	0.0345	0.00		
2000	0.0579	0.00		
2001	0.0346	0.00		
Unemployment Rate			-0.0045	0.00
N		9,377		9,377
LR chi2		763.12		754.69
Prob > chi2		0.0000		0.0000
Pseudo R2		0.1261		0.1248
Likelihood Ratio		-2643.16		-2647.38

The model results also show that workers in the building and market services sector are 5.6 per cent and 1.8 per cent respectively more likely to change jobs relative to workers in the nonmarket services sector. Workers in the agricultural, manufacturing and utilities sector are less likely to change jobs than those in the nonmarket services sector.

The year dummies are used to control for the factors that vary over time and that affect all workers. The coefficients on the year dummies are positive and significant (with the exception of the dummies for 1996 and 1997). It is likely that these year dummies are picking up the strong rise in economic and employment growth that took place towards the end of the 1990s. One would expect the mobility rate to be higher when the labour market is tight. Ideally one would like to include a variable that captures the job offer arrival rate to workers over time. Vacancy rates may be a good proxy for this variable. Unfortunately, vacancy rates are not available for this period. In Specification 2, the unemployment rate is included as an indicator of labour market tightness. This variable is included to try and capture the changes in labour market conditions over the period. The marginal effect on the unemployment rate is negative as expected and significant.

5. Decomposing the Increase in the Rate of Job Change

The job mobility rate roughly doubles over the time period under consideration. It is useful to ascertain whether this increase was driven by changes in the composition of the sample or whether it was due to other factors. One approach to doing this is to group some of the earlier years and some of the later years of my sample together and to decompose the difference in mobility rates between the two groups into the difference attributable to differences in the observable characteristics and the difference due to differences in the effects of characteristics by applying a non-linear Blinder-Oaxaca type decomposition to the estimates.

5.1 Non-Linear Decomposition Technique

I have grouped together the observations for 1995 to 1997 and for 1998 to 2001. There are 3,688 observations in the 1995-97 group and the average mobility rate is 7.5 per cent while there are 5,689 observations in the 1998-01 group and the average mobility rate is 11.4 per cent. There is a four percentage point difference in average mobility rates between the two groups. To decompose this gap between the two mobility rates, a technique developed by Fairlie (2005) is applied. The approach follows that of the Blinder-Oaxaca decomposition technique for linear models.

Consider the general case where the expected value of the dependent variable is a function of a linear combination of independent variables where the function F may or may not be linear:

$$E(Y) = F\left(X\hat{\beta}\right) \qquad (1)$$

where Y is an N $\times$ 1 vector, X is an N $\times$ K matrix of independent variables, $\hat{\beta}$ is a K$\times$1 vector of estimated coefficients and N is the sample size.

From (1) the general expression for the mean difference in the expected value of Y between two groups, say A and B can be written as:

$$\overline{Y}^A - \overline{Y}^B = \left[\overline{F\left(X^A\hat{\beta}^A\right)} - \overline{F\left(X^B\hat{\beta}^A\right)}\right] + \left[\overline{F\left(X^B\hat{\beta}^A\right)} - \overline{F\left(X^B\hat{\beta}^B\right)}\right] \qquad (2)$$

The first term in the brackets in (2) represents the part of the difference in the expected value of Y for the two groups that is due to differences in the distribution of the independent variables between the two groups; this is referred to as the "explained" component. The second term in the brackets represents differences in the processes that determine Y for the two groups.

In a linear regression model $E(Y) = F\left(X\hat{\beta}\right) = X\hat{\beta}$, the effect of X is constant so

$$\overline{Y} = \overline{F\left(X\hat{\beta}\right)} = \overline{X\hat{\beta}} = \overline{X_1\hat{\beta}_1 + X_2\hat{\beta}_2 \ldots}$$

$$= \frac{\sum_{i=1}^{N}\left(X_{1i}\hat{\beta}_1 + X_{2i}\hat{\beta}_2 + \ldots\right)}{N} = \overline{X}_1\hat{\beta}_1 + \overline{X}_2\hat{\beta}_2 + \ldots \qquad (3)$$

where i=1….n is the number of cases.

Using the expression for the general decomposition given in (2) yields the standard Blinder-Oaxaca decomposition:

$$\overline{Y}^A - \overline{Y}^B = \left[\left(\overline{X}^A - \overline{X}^B\right)\hat{\beta}^A\right] + \left[\left(\hat{\beta}^A - \hat{\beta}^B\right)\overline{X}^B\right] \qquad (4)$$

In a non-linear regression model, such as a probit model, the effect of X is not constant i.e. $\frac{dY}{dX_K} = f\left(X\hat{\beta}\right)\hat{\beta}_K$, the marginal effect of $\hat{\beta}_K$ varies with the level of X and the other variables in the model so $\overline{Y} = \overline{F\left(X\hat{\beta}\right)} \neq F\left(\overline{X}\hat{\beta}\right)$. In this case:

$$\overline{Y} = \overline{F\left(X\hat{\beta}\right)} = \overline{F\left(X_1\hat{\beta}_1 + X_2\hat{\beta}_2 + \ldots\right)}$$

$$= \frac{\sum_{i=1}^{N} F\left(X_{1i}\hat{\beta}_1 + X_{2i}\hat{\beta}_2 + \ldots\right)}{N} \qquad (5)$$

Therefore we can write:

$$\overline{Y}^A - \overline{Y}^B = \left[\sum_{i=1}^{N^A}\frac{F\left(X_i^A\hat{\beta}^A\right)}{N^A}\right] - \left[\sum_{i=1}^{N^B}\frac{F\left(X_i^B\hat{\beta}^B\right)}{N^B}\right] \qquad (6)$$

Fairlie suggests a decomposition for a non-linear regression equation, which can be written as:

$$\overline{Y}^A - \overline{Y}^B = \left[\sum_{i=1}^{N^A} \frac{F\left(X_i^A \hat{\beta}^A\right)}{N^A} - \sum_{i=1}^{N^B} \frac{F\left(X_i^B \hat{\beta}^A\right)}{N^B} \right] + \left[\sum_{i=1}^{N^B} \frac{F\left(X_i^B \hat{\beta}^A\right)}{N^B} - \sum_{i=1}^{N^B} \frac{F\left(X_i^B \hat{\beta}^B\right)}{N^B} \right] \quad (7)$$

Again, the first term in the brackets provides an estimate of the overall contribution of the independent variables to the gap in mobility rates and the second term represents the unexplained component. As with the standard Blinder-Oaxaca decomposition one can use the coefficients from Group A as weights for the first term in the decomposition or the coefficients from a pooled sample of the two groups or one can re-write the decomposition to use the coefficient estimates from Group B.

Fairlie focuses on the first part of the decomposition, which estimates the overall contribution of the independent variables to the difference in average value of the dependent variable. The change in the average value of Y is calculated by replacing the distribution of all independent variables from Group A with the distributions of all the independent variables from Group B.

The contribution of each independent variable to the overall change in the average value of the dependent variable is calculated by separately replacing the distribution of each independent variable from Group A with its distribution from Group B while holding the distribution of the other variables constant. Suppose, first of all that the sample size of both groups is the same. Then the contribution of variable X_1 to the change in the average value of Y is given by:

$$\frac{1}{N^A} \sum_{i=1}^{N^A} F\left(\hat{\beta}_0^A + X_{1i}^A \hat{\beta}_1^A + X_{2i}^A \hat{\beta}_2^A + \ldots\right) - F\left(\beta_0^A + X_{1i}^B \hat{\beta}_1^A + X_{2i}^A \hat{\beta}_2^A + \ldots\right) \quad (8)$$

To calculate the contributions of individual independent variables there needs to be a one-to-one matching of observations from both groups. To generate this matching, each person in Group A is ranked according to their predicted probability and similarly for each person in Group B. Then the person with the highest predicted probability in Group A is matched with the person with the highest predicted probability in Group B and the person with the second highest predicted probability in Group A is matched with the person with the second highest predicted probability in Group B and so on.[15]

In practice, the sample sizes of both groups will seldom be the same so to calculate the contribution of individual independent variables to the gap Fairlie suggests taking a random sample of the larger group that is equal in size to the other group. Each observation in the subsample of the larger group and the full sample of the smaller group is separately ranked by their predictive probabilities and matched by their respective rankings as before. The decomposition estimates will depend on the randomly chosen subsample. Ideally, the results should approximate those from matching all of Group A to Group B. To achieve this, lots of random subsamples from the larger group should be chosen and each of these should be matched to the smaller sample. Then separate decompositions for each subsample should be computed and

[15] As the predicted probabilities are non-linear functions of the parameter estimates standard errors for the estimates are calculated using the delta method.

the average value of the separate decompositions can be used to approximate the results for the whole of the larger group.

Table 17 presents the results of the non-linear decomposition of the difference in job mobility rates between the two periods. The coefficient estimates from the pooled sample are used to calculate the decomposition.[16] The results are based on mean values of decompositions with 100 different subsamples. The table also shows the average values of the independent variables over the two time periods.

Table 17: Non-Linear Decomposition of the Difference in Job Mobility Rates between 1995-97 and 1998-01 using the Fairlie Method

Sample used to estimate coefficients	Pooled Coefficients			
Average Mobility Rate 1995-97	**0.0748**			
Average Mobility Rate 1998-01	**0.1144**			
Difference	**0.0395**			
All Variables (Amount of Gap Explained)	**0.0087**			
Standard Error	**0.0013**			
% of Overall Gap Explained	**21.9%**			
	Contribution	$P>\|Z\|$	$\overline{X}9597$	$\overline{X}9801$
Experience	0.0061	0.43	19.9	18.7
Experience squared	-0.0032	0.66	536.1	478.0
Education- medium	-0.0015	0.07	0.38	0.46
Education- high	-0.0006	0.38	0.13	0.16
Female	-0.0004	0.59	0.33	0.37
Children	-0.0002	0.57	0.57	0.55
Married	0.0020	0.02	0.71	0.64
Public Sector	0.0021	0.02	0.31	0.27
Number of Employees	0.0003	0.61	0.36	0.34
Overskilled	-0.0014	0.00	0.48	0.46
Occupation of Origin:				
Manager	0.0021	0.00	0.11	0.09
Professional	0.0015	0.18	0.26	0.24
Clerk	-0.0015	0.05	0.22	0.25
Skilled	0.0001	0.94	0.23	0.21
Sector of Origin:				
Agriculture & Mining	0.0016	0.06	0.14	0.11
Manufacturing	-0.0001	0.94	0.18	0.19
Utilities	0.0000	0.68	0.01	0.01
Building	0.0014	0.09	0.07	0.08
Market Services	0.0005	0.46	0.34	0.36

[16] Using the coefficient estimates from 1995-97 or 1998-01 in the decomposition produces similar results.

The difference in the average value of the independent variables accounts for 22 per cent of the difference in job mobility rates over the two time periods. This means that the difference in mobility rates between the two time periods would be around 22 per cent lower if the people in the 1995-97 group had the same distribution of characteristics as the people in the 1998-01 group. In terms of individual characteristics, experience, occupation and working in the public sector are important contributors to explaining the difference in mobility rates between the two time periods. The standard errors on practically all of the individual contributions are high so we cannot say with a lot of confidence how important individual variables are. However, the standard error on the overall contribution of the independent variables is low. The results suggest that the changing composition of the sample is only driving around a fifth of the increase in job mobility over the period.

In section 2, the rising proportion of young people in the sample was put forward as a possible explanation for the rise in mobility. Including age and its square in the decomposition instead of the experience variables produces broadly similar results; the overall contribution of the independent variable rises to 27 per cent. Finally, including the unemployment rate in the model increases the proportion of the gap explained to 50 per cent. However, the fall in the unemployment rate captures the changing labour market conditions facing workers and is not related to the changing composition of the sample.

6. Conclusion

This paper has analysed job mobility in Ireland over the period 1995 to 2001 using data from the Living in Ireland Survey. It finds that there are several factors that determine mobility. Consistent with the theoretical and empirical literature in this area years of labour market experience is a key determinant of job change. Workers in the public sector are less likely to change jobs and workers who are overskilled are more likely to change jobs. It finds that gender does not affect the probability of changing jobs. Higher levels of human capital, both general human capital captured by education level and more specific human capital embodied in occupation, exert a negative influence on job mobility.

The paper also finds the rate of job mobility in Ireland practically doubled over the period. Estimation results show that workers were more likely to change jobs in the later part of the period. A decomposition analysis shows that around a fifth of this increase is driven by changes in the composition of the sample. The changing labour market conditions facing workers appear to be an important factor driving the increase. Even accounting for compositional changes and changes in the labour market, a substantial part of the increase in job mobility over the period remains unexplained.

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Appendix Table 1: Explanatory Variables: Definitions and Summary Statistics

Variable	*Description*	*Mean*	*Std. Dev.*
Experience	Number of years in employment	19.2	11.5
Education- low (Reference Category)	Dummy variable that takes the value 1 if highest educational qualification is Junior Certificate and zero otherwise	0.42	0.49
Education- medium	Dummy variable that takes the value 1 if highest educational attainment is above Junior Certificate but below degree level and zero otherwise	0.43	0.50
Education- high	Dummy variable that takes the value 1 if highest educational qualification is a degree or above and zero otherwise	0.15	0.36
Female	Dummy variable that takes the value 1 if female and zero if male	0.36	0.48
Married	Dummy variable that takes the value 1 if married and zero otherwise	0.67	0.47
Children	Dummy variable that takes the value 1 if the person has children and zero otherwise	0.56	0.50
Public	Dummy variable that takes the value one if the person was working in the public sector in the previous year and zero otherwise	0.28	0.45
Number of Employees	Dummy variable that takes the value 1 if the number of employees in the firm in the previous year is more then 50 and zero otherwise.	0.35	0.48
Overskilled	Dummy variable that takes the value 1 if the worker reported that they felt they had skills and qualifications to do a more demanding job	0.47	0.50
Occupation of Origin:			
Manager	Dummy variable that takes the value 1 if occupation of origin is manager, senior official or legislator and zero otherwise	0.10	0.29
Professional	Dummy variable that takes the value 1 if occupation of origin is professional, technician or associated professionals and zero otherwise	0.25	0.43
Clerk	Dummy variable that takes the value 1 if occupation of origin is clerk, service, shop or sale worker	0.23	0.42
Skilled	Dummy variable that takes the value 1 if occupation of origin is skilled agricultural or fishery worker or a skilled craft or trades worker and zero otherwise	0.22	0.41
Elementary (Reference Category)	Dummy variable that takes the value 1 if occupation in the previous year is plant or machine operator or assembler, or elementary occupation and zero otherwise	0.20	0.40
Sector of Origin:			
Agriculture & Mining	Dummy variable that takes the value 1 if sector of origin is agriculture, fishing, mining or quarrying and zero otherwise	0.12	0.32
Manufacturing	Dummy variable that takes the value 1 if sector of origin is manufacturing and zero otherwise	0.19	0.39
Utilities	Dummy variable that takes the value 1 if sector of origin is utilities and zero otherwise	0.01	0.10
Building	Dummy variable that takes the value 1 if sector of origin is building and zero otherwise	0.08	0.27
Market Services	Dummy variable that takes the value 1 if sector of origin is distribution, hotels and restaurants, transport, storage and communications, financial intermediation, or real estate, renting and	0.35	0.48

	business activities and zero otherwise		
Non-Market Services (Reference Category)	Dummy variable that takes the value 1 if sector or origin is education, public administration and defence or health and social work and zero otherwise	0.25	0.43
Year Dummies:			
1995 (Reference Category)	Dummy variable that takes on the value 1 if the year is 1995 and zero otherwise	0.13	
1996	Dummy variable that takes on the value 1 if the year is 1996 and zero otherwise	0.13	
1997	Dummy variable that takes on the value 1 if the year is 1997 and zero otherwise	0.14	
1998	Dummy variable that takes on the value 1 if the year is 1998 and zero otherwise	0.14	
1999	Dummy variable that takes on the value 1 if the year is 1999 and zero otherwise	0.15	
2000	Dummy variable that takes on the value 1 if the year is 2000 and zero otherwise	0.15	
2001	Dummy variable that takes on the value 1 if the year is 2001 and zero otherwise	0.16	
Unemployment Rate	ILO annual unemployment rate from the CSO	7.71	3.3