DISCUSSION PAPER SERIES

No. 2710

ESTIMATING THE WAGE COSTS OF INTER- AND INTRA-SECTORAL ADJUSTMENT

Michelle Haynes, Richard Upward
and Peter Wright

INTERNATIONAL TRADE

Centre for Economic Policy Research

www.cepr.org

Available online at: www.cepr.org/pubs/dps/DP2710.asp

ISSN 0265-8003

ESTIMATING THE WAGE COSTS OF INTER- AND INTRA-SECTORAL ADJUSTMENT

Michelle Haynes, University of Nottingham
Richard Upward, University of Nottingham
Peter Wright, University of Nottingham and CEPR

Discussion Paper No. 2710
February 2001

Centre for Economic Policy Research
90–98 Goswell Rd, London EC1V 7RR, UK
Tel: (44 20) 7878 2900, Fax: (44 20) 7878 2999
Email: cepr@cepr.org, Website: www.cepr.org

CEPR Discussion Paper No. 2710

February 2001

ABSTRACT

Estimating the Wage Costs of Inter- and Intra-Sectoral Adjustment*

The proposition that labour market adjustments to intra-industry trade are less costly than adjustments to inter-industry trade is a widely-held belief amongst trade economists. If it is the case that there are significant sector-specific skills, then this 'smooth adjustment hypothesis' seems intuitive. However, direct evidence relating to this issue remains largely anecdotal. In this Paper we adopt the methodology of the micro-econometric labour literature to estimate the returns to tenure within firms, industries and occupations in order to predict the costs, in terms of wage losses, of moving jobs between and within sectors. To do this we use a large panel of individual workers for the UK over a long period (1975–1998), which enables us to control for unobserved fixed effects which may jointly determine the propensity to move jobs and the wage level.

JEL Classification: C33, F16, J30, J62
Keywords: industry specific skills, mobility, smooth adjustment, tenure, wages

Michelle Haynes
Department of Economics
University of Nottingham
University Park
Nottingham NG7 2RD
UK
Tel: (44 115) 951 5151
Fax: (44 115) 9514159
Email: Michelle.Haynes@Nottingham.ac.uk

For further Discussion Papers by this author see:
www.cepr.org/pubs/new-dps/dplist.asp?authorid= 139800

Richard Upward
Department of Economics
University of Nottingham
University Park
Nottingham NG7 2RD
UK
Tel: (44 115) 951 5151
Fax: (44 115) 951 4159
Email: richard.upward@nottingham.ac.uk

For further Discussion Papers by this author see:
www.cepr.org/pubs/new-dps/dplist.asp?authorid= 145255

Peter Wright
Department of Economics
University of Nottingham
University Park
Nottingham NG7 2RD
UK
Tel: (44 115) 951 5470
Fax: (44 115) 951 4159
Email: Peter.Wright@nottingham.ac.uk

For further Discussion Papers by this author see:
www.cepr.org/pubs/new-dps/dplist.asp?authorid= 128260

*The authors acknowledge financial support from The Leverhulme Trust under Programme Grant F114/BF.

Submitted 23 November 2000

NON-TECHNICAL SUMMARY

The proposition that labour market adjustments to intra-industry trade are less costly than adjustments to inter-industry trade is a widely held belief amongst trade economists. This proposition is based on the idea that factors of production, such as labour, can be reallocated within industries more easily than between industries. However, empirical tests of this hypothesis have been crude and rather indirect. There is however a well-developed theoretical and empirical literature in labour economics concerned with the relationship between job tenure and wages, which has a direct bearing on this question. Returns to tenure within a firm are usually interpreted in terms of returns to specific human capital. If skills have a significant industry-specific component, this provides direct evidence that adjustment costs will be lower for workers who move jobs within industries compared to those who move jobs between industries.

It also seems reasonable to suppose that some skills may be specific to occupations, and therefore an additional question of interest is the relative importance of returns to occupational tenure. In this Paper we analyse the extent to which wages increase with tenure not only within firms, but also within industry and occupation. By doing this we are able to provide estimates of the potential ‘cost’ to workers of changing jobs, industry and occupation.

We outline the basic theory concerning the relationship between tenure and wages, and present an econometric framework for analysing this relationship. This discussion emphasizes that there are a number of reasons for believing that measuring the observed relationship between job tenure and wages might be misleading. The basic problem is that there may be unobservable factors which impact on wages that are also correlated with the included measures of tenure. This will lead to a bias in the estimated returns to staying in a firm, industry or occupation. For example, more able individuals may change jobs less often and, hence, tend to have longer tenure. Or, workers who choose to move jobs will tend to do so for higher wages. It may therefore be difficult to determine whether the observed relationship between tenure and wages is an overestimate of the true relationship because more able people are less mobile, or an underestimate because job movers do so for wage gains. Similar problems will also be associated with identifying returns to industry and occupational tenure.

Using a large panel of young workers over a long time period for the UK, our results suggest that once these biases are controlled for, returns to industry tenure are extremely small. Instead, we find that returns to occupational tenure are much larger. One interpretation of this result is that workers moving between industries suffer no greater wage losses than workers moving within industries, provided that they remain in the same occupation. We do find that

movements between less narrowly defined sectors incur greater wage losses, but these are still very small compared to the costs of switching between occupations.

In a recent comprehensive study of returns to tenure, Altonji & Williams (1997) suggest that the best estimate for returns to 10 years firm tenure is about 10%. Our results suggest that it is not firm tenure itself which causes this increase, but occupational, and to a lesser extent, industry tenure. We find no compelling evidence that the wage costs of moving between industries are necessarily larger than those of moving within industries.

1 Introduction

The proposition that labour market adjustments to intra-industry trade are less costly than adjustments to inter-industry trade is a widely-held belief amongst trade economists. This proposition is based on the idea that factors of production, such as labour, can be reallocated within industries more easily than between industries. However, as noted by Brülhart, Murphy & Strobl (1998, p.1), "there exists no formal theoretical underpinning for this assumption ... empirical tests of [this hypothesis] have been crude and rather indirect."

There is however a well-developed theoretical and empirical literature in labour economics concerned with the relationship between job tenure and wages which has a direct bearing on this question. Returns to tenure within a firm are usually interpreted in terms of returns to specific human capital.[1] Estimates of the wage returns to firm tenure are common, either by examining within-job wage growth, or by examining the changes in wages which occur when workers change jobs. As noted by Neal (1995), however, there is far less work which measures the value of industry-specific skills. If skills do have a significant industry-specific component, this provides direct evidence that adjustment costs will be lower for workers who move jobs within industries compared to those who move jobs between industries.

It also seems reasonable to suppose that some skills may be specific to occupations, and therefore an additional question of interest is the relative importance of returns to occupational tenure. This question too appears to have received little attention in the literature.

In this paper we analyse the extent to which wages increase with tenure not only within jobs, but also within industry and occupation. By doing this we are able to provide estimates of the potential 'cost' to workers of changing jobs, industry and occupation. We use a large panel dataset of UK employees over the period 1975–1995, which enables us to examine the consequence of different assumptions about likely biases which may result from correlations between the unobservable determinants of wages and the

[1]Returns to tenure are also consistent with a number of other theories of worker compensation, such as screening or signalling theories (Weiss 1995).

measures of tenure which we use. The size of the dataset also enables us to examine whether sector-specific skills vary across sectors, and whether wage changes are greater for moves between sectors defined at a more aggregate level, and which are therefore less similar.

In Section 2 we outline some basic theory about the relationship between tenure and wages, and present an econometric framework for analysing this relationship. Some previous estimates are presented in Section 3, and Section 4 describes our proposed methods. Section 5 describes the data, and our results are presented in Section 6. Section 7 concludes.

2 A framework for estimating returns to industry and occupational tenure

Workers who are involuntarily displaced from their jobs suffer wage losses, and these losses tend to be higher for more senior workers.[2] This fact lends support to the idea that part of a worker's remuneration consists of a return to tenure, and this is foregone if the employment relationship is severed. The most common explanation for these returns to tenure is that workers accumulate human capital specific to a particular job (Becker 1962). Increasing wages reflect in part increasing productivity, and also a means by which any match-specific rents generated by training are shared. General human capital, that which is not specific to a particular job, also accumulates, and this explains the positive relationship between wages and total labour market experience.

In this context, it seems natural to consider whether some proportion of the observed increase in wages with firm tenure is due to the accumulation of *industry-specific* human capital. As noted by Neal (1995, pp.653–654): "All firms in a given manufacturing industry may value a common set of skills that are vital to the production process in that industry. However, these same skills may not be valued by firms that manufacture different product lines." As well as being of importance to the individual, the extent to which

[2]Evidence for this comes from the large (mainly US) literature on displacement; Kletzer (1998) provides a summary.

skills are industry specific is clearly of great interest in determining the cost of aggregate adjustment where many workers move from one industry to another. Similarly, it seems likely that the length of time spent in an occupation is also an important factor in determining wages. It might be the case, for example, that individuals who move industries but who remain in the same occupation can achieve higher wages than those who switch occupation as well.

A simple relationship between wages, experience and tenure can be written as:

$$w_{ijt} = X_{it}\gamma_1 + T_{ijt}\gamma_2 + I_{ikt}\gamma_3 + O_{ilt}\gamma_4 + \mathbf{x}'_{ijt}\boldsymbol{\beta} + \varepsilon_{ijt}, \tag{1}$$

where w_{ijt} is the log wage for individual i on job j at time t, X_{it} is total labour market experience, T_{ijt} is firm tenure, I_{ikt} is industry tenure and O_{ilt} is occupational tenure. All these elements vary over j, but we subscript X_{it} by it to indicate that experience increases for each individual regardless of j. Similarly, I_{ikt} increases over spells within industries k and O_{ilt} increases over spells in occupations l. The precise relationship between experience and tenure is unlikely to be linear as shown above, but we leave investigation of this issue for the empirical work. $\mathbf{x}_{ijt}$ is a vector of other measurable characteristics thought to influence wages. The unmeasured component of this relationship, ε_{ijt}, can be decomposed into three separate terms:

$$\varepsilon_{ijt} = \mu_i + \phi_{ij} + \nu_{ijt}. \tag{2}$$

μ_i is the unobserved person-specific component of wages, and is assumed not to vary over time. ϕ_{ij} is the unobserved component of wages due to a specific worker-firm pair. This can be thought of as reflecting the unobserved value of a particular match between a worker and a firm. In this framework ϕ_{ij} is assumed fixed over the course of a job, although a less restrictive framework would allow ϕ_{ijt} to vary within jobs.[3] ν_{ijt} accounts for any other unobserved component of wages. There may also be an unobserved component to a particular match between a worker and an industry, or between a worker and an occupation. We propose a method for

[3]Dustmann & Meghir (1999) develop a model where different jobs offer different wage profiles.

dealing with this issue in Section 4. For simplicity in this section we assume for the moment that Equation (2) represents the true error structure.

We are interested in estimating the returns to experience and the three different forms of tenure and in particular γ_3, the returns to industry tenure. If all skills are specific only to a particular job, then $\gamma_2 > 0$ and $\gamma_3 = \gamma_4 = 0$. In this case there is no 'cost' to moving between industries or occupations above that which occurs when workers move job.

Biases will arise in the estimation of the parameters on X_{it}, T_{ijt}, I_{ikt} and O_{ilt} if a correlation exists between the unobservables and these variables. There are two important reasons why elements of ε_{ijt} might be correlated with experience and tenure in our data.

First, the unobserved person-specific effects μ_i may be correlated with experience or tenure. If workers with higher unobserved ability have lower turnover, for example, then they will tend to have higher values for tenure. Similar arguments apply to the correlation of μ_i with I_{ikt} and O_{ilt}. A correlation between 'ability' and turnover propensity does not in itself lead to any correlation between μ_i and total experience, X_{it}. But if the correlation between μ_i and tenure occurs because workers with low values of μ_i are more likely to have periods of unemployment, then ε_{ijt} would also be correlated with total experience X_{it} as well as the individual elements of tenure.[4]

Second, the worker-firm match quality ϕ_{ij} and tenure or experience may be correlated. Altonji & Shakotko (1987) argue that OLS estimates of γ_2 will be biased upwards because workers with high values of ϕ_{ij} are less likely to quit, and hence ϕ_{ij} and T_{ijt} will be positively correlated. However, Topel (1991) shows that OLS estimates will actually be biased downwards because ϕ_{ij} and T_{ijt} are negatively correlated: individuals who move jobs do so in order to obtain higher values of ϕ_{ij}, and movers have low tenure. The correlation between ϕ_{ij} and total experience X_{it} is more clear cut.

[4]The panel data we use (see Section 5) are particularly prone to individuals not being recorded in a particular year, even if they are in employment. If the probability of not being in the sample is also correlated with the unobserved fixed effect, a similar problem ensues. In the US literature it is usually assumed that $\mathrm{Cov}(\mu_i, X_{it}) = 0$, but this does not seem appropriate in this case.

Workers who have been in the labour market for longer are more likely to have received offers of jobs with high values of ϕ_{ij}, and therefore ϕ_{ij} and X_{it} will be positively correlated.

3 Some previous estimates

There is a large US literature which estimates γ_1 and γ_2. Direct estimates of Equation (1) under the assumption that $\gamma_3 = \gamma_4 = 0$ come from the literature on returns to seniority — see Altonji & Williams (1997) for a recent thorough survey, and the references therein. Alternatively, the literature on the wage effects of job displacement calculates wage changes following job moves (e.g. Kletzer 1989, Jacobson, LaLonde & Sullivan 1993). For example, a first-differenced version of Equation (1) for workers who change jobs, but remain in the same industry and occupation, yields:

$$\Delta w_{ijt} = (\gamma_1 + \gamma_3 + \gamma_4) - T_{ijt-1}\gamma_2 + \Delta \mathbf{x}'_{ijt}\boldsymbol{\beta} + \Delta\varepsilon_{ijt}, \tag{3}$$

where $\Delta w_{ijt} = w_{ijt} - w_{ijt-1}$, and T_{ijt-1} refers to tenure on the previous job at time $t-1$. In a model such as this, the cost of worker dislocation is a function of previous job tenure. Common alternative specifications regress wages on dummy variables recording displacement events in previous periods, which allow for the identification of 'scarring' effects of displacement.

In principal it makes no difference whether estimates of γ_2 are taken from Equation (1) or (3), although in practice results will depend on how the estimates deal with the possible biases resulting from the correlation of ε_{ijt} with measures of tenure. One important difference between the two methods is in the choice of sample. By definition, a sample of displaced workers have not moved voluntarily between jobs, and therefore the correlation between ϕ_{ij} and tenure is likely to be different. Indeed, it seems more plausible to assume that ϕ_{ij} and T_{ijt-1} are uncorrelated for displaced workers. The problem of a permanent ability bias μ_i still remains, however, and may be increased if workers of lower ability are more likely to be displaced.

The most common approach to the selectivity problem in the tenure-wage literature is to adopt an instrumental variables method to estimate γ_1 and

γ_2. Altonji & Shakotko (1987) show that the deviation from mean within-job tenure is a valid instrument for tenure because

$$\mathrm{Cov}((T_{ijt} - \bar{T}_{ij.}), \phi_{ij}) = 0,$$

where $\bar{T}_{ij.}$ is the within-job mean value of tenure for each individual. As noted by Williams (1991), this is almost exactly the same procedure as estimating a standard fixed-effect estimate of Equation (1) using jobs rather than individuals as the unit over which deviations from the mean are taken. The only difference being that the IV method allows for estimates of the coefficients on non time-varying parameters such as years of schooling. However, whether (1) is estimated using IV or fixed-effects, it is not possible to separately estimate all four parameters γ_1–γ_4 because experience and the three tenure measures rise together at the same rate within each job. Altonji & Shakotko obtain estimates of γ_1 by assuming $\mathrm{Cov}(X_{it}, \phi_{ij} = 0)$ and so only instrument T_{ijt}.[5]

A closely related method is provided by Topel (1991). Assuming $\gamma_3 = \gamma_4 = 0$, first-differencing Equation (1) for individuals who do not change jobs provides a consistent estimate of $\gamma_1 + \gamma_2$ because fixed individual and job effects are removed:

$$\Delta w_{ijt} = \gamma_1 + \gamma_2 + \Delta \mathbf{x}'_{ijt}\boldsymbol{\beta} + (\nu_{ijt} - \nu_{ijt-1}). \tag{4}$$

An estimate of γ_1 can then be obtained from a regression of wages in new jobs on experience:

$$w_{ijt} = X_{0ijt}\gamma_1 + \mathbf{x}'_{ijt}\boldsymbol{\beta} + \phi_{ij} + \mu_i + \nu_{ijt}, \tag{5}$$

where X_{0ijt} is experience at the beginning of a new job spell. This provides an upper-bound on the true value of γ_1 because ϕ_{ij} and X_{0ijt} are positively correlated: ϕ_{ij} and X_{0ijt} rise together if better matches are observed as time in the labour market increases. Hence a lower bound on γ_2 can be estimated from the difference between $(\widehat{\gamma_1 + \gamma_2})$ from (4) and $\hat{\gamma}_1$ from (5).

As noted in the introduction, there are few estimates of γ_3 or γ_4 in the literature: few papers estimate returns to industry tenure in addition to

[5] Altonji & Shakotko acknowledge this and estimate an additional model where $\mathrm{E}(\phi_{ij} \mid X_{it})$ is estimated using an additional equation predicting quits as a function of experience.

returns to job tenure.[6] Exceptions include Neal (1995), Parent (1995) and Kletzer (1996).[7]

Neal (1995) uses the Displaced Workers Survey (DWS) to compare, for workers who have involuntarily lost their jobs, wage changes of those who change industry and those who return to the same industry. This is equivalent to estimating Equation (3) separately for industry movers and stayers. In this framework, two possible selection biases may arise. First, it is possible that displaced workers are not a random sample of all workers. To mitigate this problem, the sample used consists only of workers who lost their jobs as a result of plant closure. Second, the decision to switch industry may be correlated with the amount of industry-specific human capital: workers with less human capital will be more likely to switch. Instead of using instruments for tenure, Neal treats this second bias as a selection problem (Heckman 1979). He estimates a selection equation using a Probit model to determine whether an individual who is displaced also changes industry. Identification of the model relies on exclusion restrictions placed on the wage regression, and to this end Neal uses the total number of jobs and the rate of job growth in the pre-displacement industry to predict the probability of moving sector. These are valid instruments if they do not also directly influence wages. Neal finds that the wage costs of switching industry is strongly correlated with predisplacment tenure. Individuals with 10 years tenure who return to the same industry receive a wage premium of about 20% over those who switch industry.

Kletzer (1996) also uses the DWS, and estimates a postdisplacement earnings function which includes an interaction term between previous firm tenure and previous industry. This is necessary because the DWS does not actually contain information on previous sectoral tenure, only on previous firm tenure. This is essentially the same method as that used by Neal (1995), but with a separate earnings function for each postdisplacement

[6] Perhaps more surprisingly there also appear to be few estimates for the UK of γ_1 and γ_2.

[7] Estimates of returns to industry-specific human capital are closely related to estimates of inter-industry wage differentials, on which there is a large literature. If workers in high wage industries tend to have longer tenure then there will be a correlation between industry tenure and wages which is unrelated to industry-specific human capital. Kim (1998) is a recent example.

industry to allow for differences in wage changes across industry. As with Neal, Kletzer uses a sample selection mechanism to allow for the fact that choice of postdisplacement sector may be correlated with postdisplacement wages.

In terms of our framework given by Equations (1) and (2), the problem of sample selection arises because there is an additional component of wages due to industry-specific match quality that is also unobserved. Equation (2) becomes

$$\varepsilon_{ijt} = \mu_i + \phi_{ij} + \eta_{ik} + \nu_{ijt}.$$

If individuals with higher values of η_{ik} are less likely to switch industry following a displacement then OLS estimates of wage changes may underestimate the effect of switching industry.

Parent (1995) uses a similar methodology to that suggested by Altonji & Shakotko, using the National Longitudinal Survey of Youth. He estimates γ_1, γ_2 and γ_3 from Equation (1), where X_{it}, T_{ijt} and I_{ikt} are replaced with instruments calculated as deviations from the mean. Crucially, separate estimates of γ_1, γ_2 and γ_3 can be recovered because $\bar{X}$, $\bar{T}$ and $\bar{I}$ are not all within-job means. Rather, $\bar{X}_{i.}$ is mean experience for each individual, $\bar{T}_{ij.}$ is mean tenure for each job and $I_{ik.}$ is mean industry tenure for each spell within an industry. This method is only appropriate if one believes that X_{it} is correlated with μ_i but not with ϕ_{ij}, and that I_{ikt} is correlated only with η_{ik} and not with ϕ_{ij}. Interestingly, Parent finds that once industry tenure is included, estimated returns to firm tenure are insignificantly different from zero.

Although they do not provide any estimates, both Neal and Parent recognise that occupations as well as industries may be important in determining the wage costs of moving jobs. It seems likely that if occupation and industry switching are correlated, some proportion of the estimated returns to industry are actually due to occupation-specific human capital. Our analysis therefore includes measures of occupational as well as industry tenure.

4 Methods

The methods used in this paper are based on those suggested by Altonji & Shakotko (1987) and Parent (1995). Consider a version of Equation (1), ignoring for the moment measures of industry and occupational tenure.

$$w_{ijt} = X_{it}\gamma_1 + T_{ijt}\gamma_2 + \mathbf{x}'_{ijt}\boldsymbol{\beta} + \varepsilon_{ijt}. \tag{6}$$

As before, we assume that the error ε_{ijt} comprises three elements:

$$\varepsilon_{ijt} = \mu_i + \phi_{ij} + \nu_{ijt}.$$

OLS estimates of γ_1 will be biased if either

$$\mathrm{Cov}(X_{it}, \mu_i) \neq 0 \text{ or } \mathrm{Cov}(X_{it}, \phi_{ij}) \neq 0,$$

and OLS estimates of γ_2 will be biased if either

$$\mathrm{Cov}(T_{ijt}, \mu_i) \neq 0 \text{ or } \mathrm{Cov}(T_{ijt}, \phi_{ij}) \neq 0.$$

Define $\tilde{X}_i = X_{it} - \bar{X}_{i.}$, where $\bar{X}_{i.}$ is the within-individual mean of X. Similarly, define $\tilde{X}_{ij} = X_{it} - \bar{X}_{ij.}$. By construction, it is the case that

$$\mathrm{Cov}(\tilde{X}_i, \mu_i) = 0,$$

and

$$\mathrm{Cov}(\tilde{T}_{ij}, \phi_{ij}) = 0.$$

Within a group (individual, job spell, industry spell or occupation spell) deviations from the mean are uncorrelated with the unobserved component of that group. It is also the case that

$$\mathrm{Cov}(\tilde{T}_{ij}, \mu_i) = 0.$$

Deviations from the mean within a job are uncorrelated with unobserved components which are fixed within individuals. Thus, if we suspect that both μ_i and ϕ_{ij} are correlated with both X_{it} and T_{ijt}, suitable instruments would be provided by $\tilde{T}_{ij}$ and $\tilde{X}_{ij}$. However, as noted in Section 3 any deviations from the mean within the same group are perfectly collinear, and so coefficients on these instruments cannot be separately identified.

To get around this problem we follow Parent (1995) and impose additional assumptions on the correlation between the unobservables and the right hand side variables. If we assume that $\mathrm{Cov}(X_{it}, \phi_{ij}) = 0$ then we can use $\tilde{X}_i$ as an instrument for X_{it} and $\tilde{T}_{ij}$ as an instrument for T_{ijt}, which are not collinear.

Now consider the role of industry and occupational tenure. The appropriate model is Equation (1):

$$w_{ijt} = X_{it}\gamma_1 + T_{ijt}\gamma_2 + I_{ikt}\gamma_3 + O_{ilt}\gamma_4 + \mathbf{x}'_{ijt}\boldsymbol{\beta} + \varepsilon_{ijt},$$

but we must now allow for the possibility that the error term has additional components due to industry or occupation-specific matches.

$$\varepsilon_{ijt} = \mu_i + \phi_{ij} + \eta_{ik} + \zeta_{il} + \nu_{ijt},$$

where k refers to industries and l to occupations. In theory, a spell in a job j will be a subset of industry spells k or occupation spells l.[8] Our strategy is to create a set of instruments

$$\begin{aligned}
\tilde{X}_i &= X_{it} - \bar{X}_{i.} \\
\tilde{T}_{ij} &= T_{ijt} - \bar{T}_{ij.} \\
\tilde{I}_{ik} &= I_{ikt} - \bar{I}_{ik.} \\
\tilde{O}_{il} &= O_{ilt} - \bar{O}_{il.}
\end{aligned} \tag{7}$$

That is, we use deviations from within-individual means as an instrument for X_{it}, deviations from within-job means as an instrument for T_{ijt}, deviations from within-industry spell means for I_{ikt} and deviations from within-occupation spell means for O_{ilt}.

This solution is not ideal, since these instruments will only be uncorrelated with ε_{ijt} if:

$$\mathrm{Cov}(X_{it}, \phi_{ij}) = \mathrm{Cov}(I_{ikt}, \phi_{ij}) = \mathrm{Cov}(O_{ikt}, \phi_{ij}) = 0,$$

[8]However, from the data, we know that there are some cases where individuals switch industries or occupations without apparently switching jobs.

but it does allow us to recover separate estimates of all four parameters γ_1–γ_4. While it is difficult to predict *a priori* the correlation between T_{ijt} and ϕ_{ij} (as discussed in Section 2), it seems likely that the quality of a particular job match increases with X_{it}, I_{ikt} and O_{ilt}. Thus we can argue that estimates of γ_1, γ_3 and γ_4 using this method are likely to be upper bounds.

5 Data

The data that we use come from the UK New Earnings Survey Panel Dataset (NESPD). The NESPD is a panel of a random sample of approximately 1% of civilian employees in employment in Great Britain from 1975 to 1998. The data are collected from employers under the Statistics of Trade Act 1947, which ensures a generally very high response rate.[9] Although the sample is large, and covers a long time period, the NESPD contains only a limited amount of information on the individuals. Most seriously, we have no information concerning educational attainment.

A second drawback to the NESPD is that the sample under-records individuals who have recently changed employers (Elias & Gregory 1994). That is, individuals not recorded in the panel in a particular year may not necessarily be unemployed or out of the labour force, but instead be employed with a new firm. Thus we can expect that measures of total labour market experience calculated from the NESPD are underestimates. Set against this, however, is the fact that the survey is carried out at a particular point in time in each year. Individuals may therefore be recorded as being employed at t and $t+1$ even if they were unemployed for some period between the two points. This will lead to overestimates of total labour market experience.

For the purposes of this study, the sample consists of all male workers who *entered* the labour market between 1975 and 1995. Although this reduces the sample size considerably, it enables us to construct a measure of total labour market experience which does not rely on making assumptions about

[9] A detailed description of the NES and the NESPD can be found in Gregory & Thomson (1990) and Elias & Gregory (1994).

time spent out of the labour market before the start of the panel in 1975.[10] We concentrate on males in this analysis because the employment records of females in the NESPD are generally thought to be less reliable. The last three years of the data (1996 to 1998) are excluded because a change of industry classification makes the calculation of a consistent measure of industry difficult.

For each individual we calculate a measure of total labour market experience, tenure in the current job with current firm, tenure in current industry and tenure in current occupation. Occupations are defined using the 22 sub-major groups of the 1980 Standard Occupational Classification (Elias & Gregory 1994, pp.49–50). Industries are defined by the 61 2-digit 1980 Standard Industrial Classification.[11] Total labour market experience X_{it} is defined as the total number of years since 1975 in the labour force. Employers are asked if each employee had been working in their present job for their present firm for more than 12 months, and job tenure, T_{ijt}, is calculated by summing these responses across years.

Similarly, by comparing occupation and industry codes between years we can determine whether an individual has moved industry or occupation, and hence calculate industry and occupational tenure, I_{ikt} and O_{ilt}. One difficulty with calculating industry and occupational tenure is the fact that individuals may return to the same industry or occupation after some period of time.[12] If industry-specific human capital does not depreciate instantaneously, then it would be appropriate to consider previous spells of industry tenure as part of current tenure. Following Parent (1995), we calculate I_{ikt} and O_{ilt} under the alternative assumptions that (a) tenure depreciates immediately on leaving an industry or occupation and (b) tenure does not depreciate at all.[13]

[10]Dustmann & Meghir (1999) note that one of the common deficiencies of data used in estimates of returns to tenure is that experience is not known before a particular date.

[11]From 1975 to 1982 the NESPD used the 1968 SIC classification; from 1982 to 1995 the 1980 SIC classification was used. Cross-coding was achieved by comparing the codes for 1982, which contained both definitions.

[12]In theory it is also possible for individuals to return to the same *firm*, but since we cannot identify which firm individuals work for, we cannot allow for this.

[13]The precise methods used for calculating X_{it}, T_{ijt}, I_{ikt}, O_{ilt} are complex and are described in detail in Upward (2000).

One drawback with models of panel data, and particularly models which rely on differencing, is that measurement error may increase the inconsistency of the estimates relative to OLS, even though the inconsistency due to correlation of μ_i and the right hand side variables is removed. This occurs because differencing data measured with error can reduce the signal-to-noise ratio of the data (Hsiao 1986, pp63–64). In our case, we might worry whether errors in recorded firm tenure, industry or occupation might bias our estimates. This will always be a problem, but there are several reasons for hoping that data from the NESPD are less prone to measurement error than other surveys. First, the data on tenure are created by cumulating year-on-year responses rather than relying on recall from more than 12 months in the past. Second, the data are collected from employers rather than employees, whom we would presume are more likely to be able to accurately describe the activity of the company. Third, the data on occupations have an inbuilt 'stability' in the sense that the worker's occupation at t was only coded as different to the occupation at $t-1$ if the respondent explicitly stated that the worker's job had changed from the previous year. Thus any measurement error in occupation is likely to have serial correlation, which as Hsiao notes, lessens the problem associated with first-differencing.

Many individuals do not have a complete work history in every year. Individuals may be missing from the panel in a particular year for a variety of reasons. First, they may be unemployed or out of the labour force. Second, they may not have been located by the survey, possibly because they recently changed employer. Third, their earnings may not have been sufficient to qualify them for income tax and National Insurance contributions, in which case they fall outside the scope of the survey. In addition, individuals may have missing information on a variable in a particular year, or their pay may have been affected by absence or part-time working. We cannot use these observations in estimates of wage equations, but it is important that they *are* used in calculation of the tenure variables. Thus, for example, we do not assume that an individual who was not in the panel at $t-1$ must have changed employer at t. In addition, we create a series of variables which record each individual's status at t and $t-1$, in case absence from the panel or missing data are correlated with earnings. These variables are described in more detail in Section 6.

Table A.1 shows the basic sample used, means of the age, tenure and experience variables and the numbers moving into and out of the panel at each point in time. The sample increases each year as new entrants enter the labour market. Individuals are classified either as new entrants, re-entrants or stayers. Re-entrants are those who are in the data at t, and who have been in the data *before* $t-1$. The sample ages as time passes, because we only observe individuals as they enter the labour market from 1975 onwards. Thus in 1975 everyone is aged 16. As a result, average measures of experience and tenure also increase over time. Total experience must increase faster than any of the other measures. The average tenure within an industry is slightly longer than average tenure within an occupation, which is slightly longer again than average job tenure.[14] Changes between jobs are therefore the most common occurrence, followed by changes between occupation, and finally changes between industry.

Some descriptive statistics are shown in Table A.2. The total sample consists of 53,332 individuals, who are in the panel (on average) for 8.3 years. About 7.4 years of this time are spent in the labour market. Note that the number of person-years is not given by the product of the number of individuals and average labour market experience, as might be expected, because the number of person-years excludes years with missing data or where pay was affected by absence. The average probability of starting a new job is 0.176. This probability falls sharply with age and tenure, as does the probability of switching industry or occupation, which are both around 11% per year.[15]

The final panel of Table A.2 shows the joint probabilities of moving between jobs, industries and occupations. Of the 17.6% who move job, 9.7% (5.8% + 3.9%) remain in the same industry and 8.7% (5.8% + 2.9%) remain in the same occupation. More surprising is the fact that of the 82.5% who do *not* change jobs, 3.3% appear to change industry. Although it is possible

[14] Of course, industrial and occupational tenure depend on the definitions of industries and occupations.

[15] To calculate the probability of starting a new job, industry or occupation we use only 'stayers', since we cannot determine precisely when a re-entrant switches industry or occupation.

that a firm's activity changed between years, this seems unlikely and we suspect that this is evidence of measurement error.[16]

Some simple evidence on the relationship between earnings and the constructed measures of tenure is presented in Table A.3. This shows the average change in log wages for movers and stayers between jobs, industries and occupations, split by the appropriate tenure of the previous spell of employment. The measure of earnings used is gross hourly earnings, including overtime payments and overtime hours. The difference between the wage changes for movers and stayers is a raw difference-in-difference estimate of the parameters γ_2, γ_3 and γ_4, without controlling for any observable characteristics or selection bias. Average wage changes for movers and stayers decline strongly with tenure, partly because of age effects. More importantly, wage changes for movers are almost always positive and *greater* than wage changes for stayers. This strongly suggests that the majority of these job changes are quits rather than layoffs, and that among young workers mobility is associated with greater wage increases. As argued in Section 2, this does not imply that returns to tenure are negative, but rather that sample selection characterises the data: movers change jobs because of higher wages available elsewhere.

6 Results

6.1 OLS estimates

A straightforward starting point for the estimation of γ_3 is to estimate Equation (1) by OLS. However, some care needs to be taken in dealing with time, age and cohort effects, and in the specification of the vector $\mathbf{x}_{ijt}$ which contains other elements thought to influence wages.

We begin by splitting the data into cohorts: the oldest cohort are 16 in 1975, the youngest are 16 in 1995. The most unrestricted specification

[16] We checked to see whether a large proportion of these industry switchers changed back to their original industry at $t+1$, which would be convincing evidence that the switch at t was caused by miscoding of industry. In fact, only 11% are coded as returning to the original industry at $t+1$.

would allow for different effects of tenure on wages across different cohorts and ages.[17] This involves estimating Equation (1) separately for each age and cohort. Exploratory results suggest that there are strong differences in estimates of γ_1, γ_2, γ_3 and γ_4 between those aged 16–20 and other ages. Cohort (or year) effects are less important. For the purposes of simplicity, we therefore group together cohorts and age groups, and exclude individuals aged 20 and under. We then include a full set of age and year dummies in the vector $\mathbf{x}_{ijt}$.

In all the following reported results, the vector $\mathbf{x}_{ijt}$ contains age dummies, year dummies, sector (public or private), union coverage, occupation (dummies for 22 major groups), industry (10 dummies) and region (10 dummies). In order to control for any possible effects from non-appearance in the panel in the previous year, $\mathbf{x}_{ijt}$ also includes four additional dummies for new entrants and re-entrants, as follows.

New entrants to the panel will by definition have experience and all measures of tenure set to one, but we also include a dummy variable "New entrant" to determine whether there is an additional effect on wages in the first year of employment. The dummy "Re-entrant" is a crude measure of recent unemployment experience which records whether an individual was not in the data at $t-1$, but is not a new entrant. Table A.1 shows that about 10% of the sample in each year are not in the sample in the previous year, which we know from other data is an overestimate of the proportion who were unemployed at $t-1$.[18] "Stayer (1)" is the base group and denotes individuals who appear in the data at $t-1$ and t and who have no missing data. "Stayer (2)" records whether an individual was in the data at $t-1$, but had missing data. Individuals who have missing values for any variables cannot be included in any regressions, and we wish to control for the possibility that the occurrence of missing values is correlated with wages. Finally, "Stayer (3)" records whether individuals were in the data at $t-1$, but had a different employment status. These individuals were either working part-time or had pay affected by absence at $t-1$.

[17] A particular cohort-age combination identifies a particular year.

[18] Gregory & Jukes (1997) provide more evidence and additional data on the effects of recent unemployment experience on wages using this data.

Table A.4 reports OLS estimates of a variety of specifications for Equation (1). The simplest estimate, specification A, is included for comparison with other work which does not include measures of industrial and occupational tenure. As expected, returns to experience and job tenure are positive, although returns to experience are far higher. These results suggest returns of 23% to 10 years labour market experience, but only 3% to 10 years job tenure. This second estimate is far lower than the typical estimate obtained from US data, which is usually estimated to be in the region of 30% from OLS regressions. A plausible explanation for this difference is that we are estimating returns to *job* tenure rather than returns to firm tenure. The precise question in the NES reads “How long has this employee worked in this **same job** in your organisation?” (original emphasis). Thus any promotions within firms will cause the tenure measure to be reset. Since, invariably, workers who are promoted will receive wage increases we have an extreme case of downward bias on γ_2.

All four dummy variables which record reasons for missing data at $t-1$ have significant and negative coefficients. Individuals who have not been in the panel before earn 2% less,[19] after controlling for age, while individuals who were missing from the panel at $t-1$ (and who may therefore have been unemployed) earn nearly 6% less. The significant coefficient on “Stayer (2)” suggests that missing data is non-random in relation to wages: individuals with missing wage data at $t-1$ earn 2.4% less. Finally, the coefficient on “Stayer (3)” shows that the effect of working part-time or having pay affected by absence at $t-1$ is to reduce wages at t by over 7%.

In specifications B–D we include more variables to test how robust these results are, and to include measures of industry and occupational tenure. An obvious problem with specification A is that it does not include measures of education, which may well be correlated with tenure and experience. Our prior would be that individuals with later school-leaving ages will have lower average experience and longer average tenure. In specification B we introduce a measure of the age when each individual first entered the panel. This is intended to proxy time spent in education, since individuals with more education will tend to enter later. Of course, it might also be the

[19]The precise effect of an estimated coefficient $\hat{\beta}$ is given by $\exp(\beta) - 1$.

case that individuals who enter late do so because they have been unemployed. However, the estimated coefficient on this variable is positive and significant, supporting the idea that later entrants do better. If those with more education also have longer job tenure, we would expect the returns to tenure to fall when we include this variable, and this is the case. Conversely, those who enter the labour force later will tend to have less total experience, and so the inclusion of this variable increases estimated returns to tenure.

In specification C we introduce our measures of industry tenure. The inclusion of these terms completely wipes out any job tenure effect. Clearly industry and job tenure are highly correlated, but it appears to be the industry effect which dominates. In specification D we also include occupational tenure, which serves to drive down returns to job tenure even further. Finally, in specification E we estimate the model using the alternative definition of industry and occupational tenure (see Page 13), which has very little effect on the estimates.

The results from specification E are summarised in the first column of Table A.6. We predict returns to 10 years of industry tenure of 10%, and returns to 10 years of occupational tenure of 12%. Note that estimates of returns to job tenure are actually negative, highlighting the fact that individuals who remain in a particular job are actually earning less than those who move jobs. These results suggest that the greatest wage gains accrue to those who move jobs within firms or within sectors and occupations.

6.2 Correlation between unobservables and tenure

The OLS results in Table A.4 may suffer from the various potential biases outlined in Sections 2 and 3. In this section we use the methods described in Section 4 to investigate whether there is any evidence that unobservables in Equation (2) are correlated with our measures of experience and tenure.

Specification F, shown in Table A.5, estimates a standard IV (2SLS) model on the pooled data, where measures of experience and tenure are instrumented by deviations from the within-individual mean. This will remove any bias arising from the correlation between μ_i and the measures of experience and tenure. To allow for the serial correlation of the within-individual errors the model is estimated with robust standard errors (White 1980).[20] The effects can most clearly be seen in column 2 of Table A.6. Returns to 10 years labour market experience are more than double the OLS estimates. This seems likely to be the result of the fact that the OLS estimates do not control for education. Individuals with higher educational attainment will have lower experience, *ceteris parabus* and higher earnings. Instrumenting X_{it} with $\tilde{X}_i$ removes individual unobserved time-invariant characteristics such as years of schooling, and so increases returns to labour market experience.

Returns to job and occupational tenure are largely unchanged from the OLS estimates, while returns to industry tenure are greatly reduced. This would suggest that the correlation between μ_i and I_{ikt} is positive, while the correlation between μ_i and T_{ijt} and O_{ilt} is less important. After removing individual-specific fixed effects it appears that returns to 10 years in the same occupation tenure are far more important (at about 13%) than returns to industry tenure (3%).

In specification G we estimate the model using the instruments in Equation 7. If the correlation between any measure of tenure and the match-specific unobservable for that tenure type is positive, we would expect specification G to return smaller estimates than specification F. Column 3 of Table A.6 summarises these results. The effect of using $\tilde{T}_{ij}$ rather than $\tilde{T}_i$ as an instrument for job tenure is to reduce the (already negative) returns to T even further, suggesting that the match-specific unobservable for job matches is indeed positively correlated with T. The negative returns to job tenure of approximately -1% per year may reflect real wage cuts for individuals staying in exactly the same job. Alternatively, they suggest that there is some additional unobserved component of earnings which is (negatively) correlated with job tenure which we have failed to control for.

Returns to industry tenure are also reduced further by the use of $\tilde{I}_{ik}$ as an instrument rather than $\tilde{I}_i$, and become extremely small. These results

[20]We regard this as more reliable than estimating a GLS model which imposes additional restrictions on the error structure.

suggest that even individuals who have been in an industry for 10 years lose only 1.2% of their earnings from switching industry. In contrast, individuals who switch occupation after 15 years lose nearly 15%. This seems intuitively sensible if we think that "skills" are associated with occupations rather than industries.

6.3 Variation in results by industry definition

Are these results dependent on the definitions of industries used? In this section we investigate whether the size of the returns to industry tenure are affected by the degree of aggregation in industry definition. It seems possible that some of the two-digit industries used here do share skills, production processes and so on, and this might explain why we find such small effects from inter-industry mobility. Moves between more disparate industries should in theory produce greater wage losses, and evidence of this would provide more support for the notion of industry-specific skills.

In specification H we re-estimate our preferred specification G using the 10 1-digit industries rather than 61 2-digit industries. Predicted returns are summarised in the final column of Table A.6. As expected, the effect of using less narrowly defined industries is to increase returns to industry tenure substantially, although the total effect is still small, estimated at less than 6% after 10 years in an industry. Returns to industry tenure are still much smaller than returns to occupational tenure.

6.4 Variation in results across sectors

The models estimated so far constrain returns to industry tenure to be the same in all industries. It seems plausible that some industries might value industry-specific skills more than others. In Table A.7 we report estimates of specifications E and H split by 1-digit industry. The average returns to industry tenure reported in previous sections disguise a lot of variation, although it is still the case that after adopting 2SLS methods returns to industry tenure are either small or insignificantly different from zero. Despite the extremely large sample size it is difficult to produce more precise estimates at this level of disaggregation. In every case apart from two the 2SLS estimates are smaller than the OLS estimates, as we would expect. The only industries with significant positive returns to industry tenure are in the service sector.

7 Conclusions

Almost all previous estimates of the effects of seniority on wages, and hence on the relationship between seniority and wage loss following displacement, have concentrated on total labour market experience and firm tenure. But it seems plausible that some skills are specific to industries and occupations as well as to individual firms. If this is the case, then workers who move between industries or occupations will experience greater wage losses than those who change jobs within sectors, and this loss will increase with industry and occupational tenure. This idea is central to the "smooth adjustment hypothesis", which argues that factors of production, such as labour, can be reallocated within industries more easily than they can be reallocated between industries.

Using a large panel of young workers over a long time period for the UK, our results suggest that once the correlation between industry tenure and unobserved match-specific components of the wage are controlled for, returns to industry tenure are extremely small. Instead, we find that returns to occupational tenure are much larger. One interpretation of this result is that workers moving between industries suffer no greater wage losses than workers moving within industries, provided that they remain in the same occupation. Of course, as Table A.2 shows, workers moving between industries are more likely to move occupation as well. We do find that movements between less narrowly defined sectors incur greater wage losses, but these are still very small compared to the costs of switching between occupations.

We also find that returns to *job* tenure are much smaller than returns to firm tenure, which is the usual measure in the literature. This is unsurprising, since a 'job' may be associated with a particular nominal wage, and so longer tenure in a particular job may lead to a declining real wage.

In a recent comprehensive study of returns to tenure, Altonji & Williams (1997) suggest that the best estimate for returns to 10 years firm tenure is about 0.11. Our results suggest that it is not firm tenure itself which causes this increase, but occupational, and to a lesser extent, industry tenure. We have failed, however, to find compelling evidence that the wage costs of moving between industries are necessarily larger than those of moving within industries.

References

Altonji, J. & Shakotko, R. (1987), "Do wages rise with seniority?", *Review of Economic Studies* **LIV**, 437–459.

Altonji, J. & Williams, N. (1997), "Do wages rise with job seniority? a reassessment", NBER working paper 6010.

Becker, G. (1962), "Investment in human capital: a theoretical analysis", *Journal of Political Economy* **70 (Sup.)**, 9–49.

Brülhart, M., Murphy, A. & Strobl, E. (1998), "Intra-industry trade and job turnover", Centre for Research on Globalisation and Labour Markets, Research paper 98/4, University of Nottingham.

Dustmann, C. & Meghir, C. (1999), "Wages, experience and seniority", CEPR Discussion Paper 2077.

Elias, P. & Gregory, M. (1994), "The changing structure of occupations and earnings in Great Britain, 1975–1990: an analysis based on the New Earnings Survey Panel Dataset", Department of Employment Research Series no. 27.

Gregory, M. & Jukes, R. (1997), "The effects of unemployment on subsequent earnings: a study of British men 1984–1994", CEP/Institute of Economics and Statistics *Labour Market Consequences of Technical and Structural change*, Discussion Paper 21.

Gregory, M. & Thomson, A., eds (1990), *A Portrait of pay, 1970-1982 :an analysis of the New Earnings Survey*, Oxford: Clarendon Press.

Heckman, J. (1979), "Sample selection bias as a specification error", *Econometrica* **87**, s213–s226.

Hsiao, C. (1986), *Analysis of Panel Data*, Cambridge: Cambridge University Press.

Jacobson, L., LaLonde, R. & Sullivan, D. (1993), "Earnings losses of displaced workers", *American Economic Review* **83**, 685–709.

Kim, D. (1998), "Reinterpreting industry premiums: match-specific productivity", *Journal of Labor Economics* **16**(3), 479–504.

Kletzer, L. (1989), "Returns to seniority after permanent job loss", *American Economic Review* **79**, 536–543.

Kletzer, L. (1996), "The role of sector-specific skills in postdisplacement earnings", *Industrial Relations* **35**, 473–490.

Kletzer, L. (1998), "Job displacement", *Journal of Economic Perspectives* **12**, 115–136.

Neal, D. (1995), "Industry-specific human capital: evidence from displaced workers", *Journal of Labor Economics* **13**, 653–677.

Parent, D. (1995), "Industry-specific capital and the wage profile: evidence from the NLSY and the PSID", Princeton University Industrial Relations Section Working paper 350.

Topel, R. (1991), "Specific capital, mobility and wages: wages rise with seniority", *Journal of Political Economy* **99**(1), 145–176.

Upward, R. (2000), "Constructing measures of experience and tenure from the nespd", Mimeo, Centre for Research on Globalisation and Labour Markets, University of Nottingham.

Weiss, A. (1995), "Human capital vs. signalling explanations of wages", *Journal of Economic Perspectives* **9**(4), 133–154.

White, H. (1980), "A heteroskedasticity-consistent covariance matrix estimator and a direct test for heteroskedasticity", *Econometrica* **48**, 817–830.

Williams, N. (1991), "Reexamining the wage, tenure and experience relationship", *The Review of Economics and Statistics* **73**, 512–517.

Table A.1: NESPD sample used 1975–1995

Year	*N*	*New entrants*	*Re-entrants*	*Stayers*	*Age*		*Total experience*		*Job tenure*		*Ind. tenure*[a]		*Ind. tenure*[b]		*Occ. tenure*[a]		*Occ. tenure*[b]	
					Mean	*SD*	*Mean*	*SD*	*Mean*	*SD*	*Mean*	*SD*	*Mean*	*SD*	*Mean*	*SD*	*Mean*	*SD*
75	717	1.000	0.000	0.000	15.99	(0.08)	1.00	(0.00)	1.00	(0.00)	1.00	(0.00)	1.00	(0.00)	1.00	(0.00)	1.00	(0.00)
76	1697	0.681	0.000	0.319	16.58	(0.50)	1.33	(0.47)	1.23	(0.42)	1.28	(0.45)	1.28	(0.45)	1.26	(0.44)	1.26	(0.44)
77	2774	0.519	0.027	0.453	17.16	(0.80)	1.68	(0.76)	1.48	(0.70)	1.56	(0.73)	1.56	(0.73)	1.52	(0.71)	1.52	(0.71)
78	4032	0.450	0.054	0.496	17.69	(1.09)	2.01	(1.02)	1.64	(0.91)	1.76	(0.96)	1.76	(0.96)	1.71	(0.94)	1.71	(0.94)
79	5551	0.393	0.072	0.535	18.19	(1.36)	2.32	(1.25)	1.77	(1.08)	1.93	(1.15)	1.93	(1.16)	1.87	(1.13)	1.88	(1.13)
80	6970	0.325	0.091	0.584	18.77	(1.64)	2.70	(1.49)	1.95	(1.23)	2.10	(1.34)	2.12	(1.35)	2.01	(1.31)	2.04	(1.33)
81	8003	0.244	0.112	0.643	19.44	(1.89)	3.21	(1.72)	2.27	(1.43)	2.43	(1.54)	2.48	(1.56)	2.30	(1.49)	2.37	(1.51)
82	9165	0.193	0.098	0.708	20.22	(2.07)	3.75	(1.95)	2.56	(1.64)	2.80	(1.75)	2.87	(1.78)	2.65	(1.69)	2.74	(1.72)
83	10731	0.223	0.098	0.679	20.80	(2.34)	4.04	(2.26)	2.66	(1.86)	2.83	(1.99)	2.99	(2.05)	2.86	(1.92)	2.96	(1.96)
84	12020	0.187	0.108	0.705	21.39	(2.57)	4.44	(2.51)	2.90	(2.07)	3.07	(2.18)	3.23	(2.26)	3.14	(2.14)	3.26	(2.18)
85	12906	0.167	0.113	0.721	22.06	(2.81)	4.87	(2.79)	3.10	(2.28)	3.33	(2.39)	3.51	(2.49)	3.37	(2.38)	3.52	(2.44)
86	15029	0.164	0.130	0.706	22.67	(3.05)	5.22	(3.04)	3.22	(2.47)	3.44	(2.63)	3.65	(2.73)	3.51	(2.59)	3.68	(2.65)
87	16697	0.160	0.123	0.718	23.24	(3.30)	5.51	(3.32)	3.30	(2.65)	3.50	(2.81)	3.74	(2.94)	3.59	(2.77)	3.79	(2.86)
88	19576	0.164	0.130	0.705	23.76	(3.57)	5.73	(3.58)	3.25	(2.77)	3.45	(2.98)	3.73	(3.12)	3.58	(2.93)	3.81	(3.03)
89	21233	0.137	0.125	0.737	24.34	(3.80)	6.13	(3.78)	3.24	(2.88)	3.44	(3.12)	3.76	(3.28)	3.64	(3.05)	3.91	(3.17)
90	22744	0.136	0.116	0.748	24.90	(4.04)	6.50	(4.02)	3.28	(2.97)	3.67	(3.23)	4.00	(3.41)	3.74	(3.18)	4.03	(3.31)
91	23628	0.092	0.116	0.791	25.66	(4.21)	7.12	(4.20)	3.49	(3.09)	4.04	(3.39)	4.39	(3.59)	3.88	(3.31)	4.39	(3.55)
92	23445	0.059	0.112	0.828	26.50	(4.31)	7.82	(4.33)	3.88	(3.19)	4.55	(3.54)	4.95	(3.73)	4.35	(3.42)	4.89	(3.67)
93	24212	0.061	0.122	0.817	27.26	(4.46)	8.43	(4.53)	4.21	(3.38)	4.94	(3.74)	5.36	(3.94)	4.69	(3.59)	5.28	(3.86)
94	25490	0.062	0.130	0.808	27.95	(4.63)	8.92	(4.76)	4.39	(3.56)	5.22	(3.94)	5.67	(4.15)	4.95	(3.78)	5.57	(4.05)
95	28239	0.071	0.120	0.810	28.62	(4.85)	9.30	(5.04)	4.48	(3.74)	5.37	(4.17)	5.88	(4.39)	5.02	(3.96)	5.69	(4.26)

[a] Calculated assuming that industry and occupational tenure are entirely lost when a spell in that industry or occupation ends.
[b] Calculated assuming that industry and occupational tenure are retained when a spell in that industry or occupation ends.

Table A.2: Descriptive statistics

Total person-years	294,859
Number of individuals i	53,332
Number of job spells j	112,268
Average number of years in panel	8.317
Average labour market experience $\bar{X}$	7.387
Average job tenure $\bar{T}$	3.055
Average industry tenure $\bar{I}$:	
(a) Assuming tenure ends at end of spell	3.420
(b) Assuming tenure is carried over	3.785
Average occupation tenure $\bar{O}$:	
(a) Assuming tenure ends at end of spell	3.415
(b) Assuming tenure is carried over	3.916
New job	0.176
New industry	0.111
New occupation	0.110
Same job, same industry, same occupation	0.775
Same job, same industry, new occupation	0.017
Same job, new industry, same occupation	0.029
Same job, new industry, new occupation	0.004
New job, same industry, same occupation	0.058
New job, same industry, new occupation	0.039
New job, new industry, same occupation	0.027
New job, new industry, new occupation	0.051

Table A.3: Wage changes of individuals changing jobs

	$\ln(w_t) - \ln(w_{t-1})$					
Years of tenure on previous job[a]	*Same Job*	*New Job*	*Same Industry*	*New Industry*	*Same Occupation*	*New Occupation*
1	0.105	0.144	0.124	0.152	0.125	0.160
2	0.084	0.130	0.096	0.118	0.095	0.134
3	0.068	0.121	0.078	0.104	0.075	0.122
4	0.056	0.105	0.064	0.083	0.062	0.095
5	0.037	0.078	0.045	0.075	0.045	0.086
5–10	0.031	0.067	0.038	0.054	0.035	0.068
10–15	0.021	0.054	0.028	0.004	0.024	0.061
15–20	0.007	−0.034	0.018	−0.083	0.012	0.055

[a] Tenure on previous job refers to firm tenure for those changing firm, occupational tenure for those changing occupation, and industry tenure for those changing industry.

Table A.4: OLS estimates

	(A)		*(B)*		*(C)*		*(D)*		*(E)*[c]	
Experience	0.0571	[0.000]	0.0604	[0.000]	0.0568	[0.000]	0.0539	[0.000]	0.0528	[0.000]
Experience^2/10	−0.0446	[0.000]	−0.0428	[0.000]	−0.0409	[0.000]	−0.0387	[0.000]	−0.0394	[0.000]
Experience^3/100	0.0107	[0.000]	0.0101	[0.000]	0.0092	[0.000]	0.0086	[0.000]	0.0090	[0.000]
Job tenure	0.0097	[0.000]	0.0084	[0.000]	0.0004	[0.819]	−0.0114	[0.000]	−0.0122	[0.000]
Job tenure^2/10	−0.0078	[0.004]	−0.0059	[0.028]	−0.0026	[0.391]	0.0084	[0.012]	0.0091	[0.004]
Job tenure^3/100	0.0013	[0.265]	0.0007	[0.524]	0.0001	[0.921]	−0.0030	[0.033]	−0.0032	[0.019]
Industry tenure					0.0195	[0.000]	0.0280	[0.000]	0.0303	[0.000]
Industry tenure^2/10					−0.0111	[0.000]	−0.0263	[0.000]	−0.0246	[0.000]
Industry tenure^3/100					0.0032	[0.011]	0.0077	[0.000]	0.0062	[0.000]
Occupation tenure							0.0134	[0.000]	0.0161	[0.000]
Occupation tenure^2/10							−0.0058	[0.065]	−0.0088	[0.004]
Occupation tenure^2/100							0.0018	[0.176]	0.0030	[0.015]
Age first entered panel			0.0067	[0.000]	0.0074	[0.000]	0.0076	[0.000]	0.0093	[0.000]
New entrant	−0.0209	[0.000]	−0.0411	[0.000]	−0.0287	[0.000]	−0.0184	[0.000]	−0.0174	[0.000]
Re-entrant	−0.0598	[0.000]	−0.0520	[0.000]	−0.0370	[0.000]	−0.0276	[0.000]	−0.0304	[0.000]
Stayer (2)	−0.0244	[0.000]	−0.0240	[0.000]	−0.0221	[0.000]	−0.0211	[0.000]	−0.0210	[0.000]
Stayer (3)	−0.0750	[0.000]	−0.0758	[0.000]	−0.0650	[0.000]	−0.0571	[0.000]	−0.0583	[0.000]
Sample size	220413									
Number of individuals	45286									
R^2	0.5034		0.5046		0.5078		0.5090		0.5109	
MSE	0.2982		0.2978		0.2969		0.2965		0.2959	

[a] All standard errors are robust (White 1980).

[b] All regressions also include age, year, occupation, industry, region, public sector and union coverage dummy variables.

[c] Specification E is identical to D, but uses different assumptions about depreciation of industry and occupation-specific human capital (see Page 13).

Table A.5: Comparison of IV estimates

	2-digit industries				1-digit industries	
	2SLS (F)		*2SLS (G)*		*2SLS (H)*	
Experience	0.1074	[0.000]	0.1168	[0.000]	0.1120	[0.000]
Experience^2/10	−0.0714	[0.000]	−0.0752	[0.000]	−0.0762	[0.000]
Experience^3/100	0.0185	[0.000]	0.0192	[0.000]	0.0199	[0.000]
Firm tenure	−0.0022	[0.171]	−0.0175	[0.000]	−0.0172	[0.000]
Firm tenure^2/10	−0.0046	[0.072]	0.0082	[0.002]	0.0066	[0.012]
Firm tenure^3/100	0.0009	[0.400]	−0.0027	[0.014]	−0.0019	[0.074]
Industry tenure	0.0063	[0.000]	0.0028	[0.181]	0.0039	[0.078]
Industry tenure^2/10	−0.0060	[0.017]	−0.0032	[0.237]	0.0029	[0.287]
Industry tenure^3/100	0.0026	[0.008]	0.0016	[0.122]	−0.0013	[0.186]
Occupation tenure	0.0301	[0.000]	0.0344	[0.000]	0.0338	[0.000]
Occupation tenure^2/10	−0.0223	[0.000]	−0.0270	[0.000]	−0.0281	[0.000]
Occupation tenure^2/100	0.0055	[0.000]	0.0074	[0.000]	0.0080	[0.000]
Age first entered panel	0.0200	[0.000]	0.0213	[0.000]	0.0203	[0.000]
New entrant	0.0344	[0.000]	0.0295	[0.000]	0.0264	[0.000]
Re-entrant	−0.0015	[0.748]	−0.0054	[0.262]	−0.0075	[0.116]
Stayer (1)	−0.0184	[0.000]	−0.0202	[0.000]	−0.0198	[0.000]
Stayer (2)	−0.0498	[0.000]	−0.0543	[0.000]	−0.0538	[0.000]
Sample size	220413					
Number of individuals	45286					
R^2	0.4983		0.4930		0.4976	
MSE	0.2997		0.3013		0.2999	

[a]Standard errors are robust (White 1980).

[b]All regressions also include age, year, occupation, industry, region, public sector and union coverage dummy variables.

Table A.6: Predicted returns to experience and tenure

		2-digit industries			*1-digit industries*
		OLS (E)	*2SLS (F)*	*2SLS (G)*	*2SLS (H)*
Return to experience	5 years	0.177 (0.007)	0.382 (0.018)	0.420 (0.019)	0.394 (0.019)
	10	0.224 (0.008)	0.545 (0.030)	0.608 (0.032)	0.556 (0.032)
	15	0.211 (0.010)	0.629 (0.041)	0.707 (0.043)	0.634 (0.044)
	20	0.203 (0.019)	0.771 (0.054)	0.862 (0.057)	0.779 (0.057)
Return to job tenure	5	−0.042 (0.004)	−0.022 (0.004)	−0.070 (0.005)	−0.072 (0.005)
	10	−0.062 (0.005)	−0.059 (0.005)	−0.121 (0.006)	−0.126 (0.006)
	15	−0.084 (0.009)	−0.106 (0.008)	−0.171 (0.009)	−0.177 (0.009)
	20	−0.132 (0.026)	−0.155 (0.021)	−0.242 (0.022)	−0.238 (0.021)
Return to industry tenure	5	0.062 (0.005)	0.020 (0.005)	0.008 (0.006)	0.025 (0.007)
	10	0.104 (0.006)	0.029 (0.006)	0.012 (0.008)	0.055 (0.009)
	15	0.146 (0.008)	0.048 (0.008)	0.025 (0.011)	0.079 (0.012)
	20	0.212 (0.023)	0.096 (0.019)	0.058 (0.021)	0.088 (0.020)
Return to occupational tenure	5	0.098 (0.005)	0.102 (0.005)	0.114 (0.007)	0.108 (0.007)
	10	0.119 (0.006)	0.133 (0.006)	0.148 (0.009)	0.136 (0.009)
	15	0.111 (0.008)	0.136 (0.008)	0.158 (0.012)	0.143 (0.012)
	20	0.121 (0.022)	0.151 (0.018)	0.199 (0.022)	0.189 (0.022)

Table A.7: Predicted returns to industry tenure by industry

		Predicted return to 10 years tenure			
		OLS (E)		*2SLS (H)*	
0	Agriculture, forestry & fishing	−0.046	(0.056)	0.109	(0.198)
1	Energy & water supplies	0.204	(0.029)	0.039	(0.061)
2	Extraction of minerals & ores other than fuels; manufacture of metals, mineral products & chemicals	0.176	(0.021)	−0.032	(0.013)
3	Metal goods, engineering & vehicles industries	0.102	(0.012)	0.013	(0.023)
4	Other manufacturing industries	0.116	(0.017)	−0.092	(0.032)
5	Construction	0.058	(0.018)	0.004	(0.042)
6	Distribution, hotels & catering (repairs)	−0.041	(0.014)	−0.053	(0.029)
7	Transport & communication	0.087	(0.016)	0.008	(0.028)
8	Banking, finance, insurance, business services & leasing	0.242	(0.018)	0.191	(0.031)
9	Other services	0.061	(0.014)	0.120	(0.025)