Human Capital Wage Premia and Unionism:

The Case of the British Labour Market in the 1990s

by

Alexandros Zangelidis

Doctor of Philosophy in Economics

University of Warwick, Department of Economics

September 2003

To my family, Mary, Nikos and Alina, and my partner Vivi for their love, support and inspiration!

Table of Contents

List of Tables

Chapter 2

Chapter 4

List of Figures

Chapter 2

Chapter 4

Acknowledgements

I am grateful to my thesis advisors, Mark Stewart and Robin Naylor, for their invaluable assistance, guidance and support in writing the thesis. I should like to thank also my two PhD examiners Erling Barth and Jeff Frank; and Omar Arias, Kevin F. Hallock, Walter Sosa-Escudero and Dimitris Georgarakos for their useful suggestions. For helpful comments, I thank seminar participants at Warwick and Paris 1, and audiences at the 16th ESPE conference, the 57th ESEM meeting and the 2003 RES annual conference. The BHPS data used in this thesis were collected by the ESRC Research Centre on Micro-Social Change at the University of Essex and made available through the ESRC Data Archive. Research support granted by ESRC (Fund No: R00429934482) is kindly acknowledged. The views expressed throughout the thesis are those of the author, and any remaining errors are solely his responsibility.

Declaration

I hereby declare that the thesis is the author's own work and it has not been submitted for a degree at another University.

Abstract

The significance of seniority for individuals' wage growth has been a very popular topic in labour economics for the past three decades. The extent to which wages rise with employer-tenure is fundamental in the understanding of the dynamics of earnings and labour market behaviour. This thesis is an empirical study of the British labour market in the 1990s and attempts to shed some light on the different kinds of skills individuals acquire in work, and their contribution to the wage determination process. Specifically, the author examines the role of seniority and employer-specific skills in earnings and explores whether industry and occupational specificity in the accumulated human capital can explain part of the variation in wages. Furthermore, the author investigates the interaction of institutional arrangements with these human capital wage premia, giving a particular attention to union representation. Throughout the empirical analysis, the issue of potential endogeneity bias in the estimates of interest is also addressed and alternative estimators are employed for that purpose. For part of the workforce, mainly in '*blue-collar*' and low-paying jobs, employer-tenure appears to have a significant impact on wage progression, which is further strengthened when employed in a more structured environment, like in the union sector, with well-set promotion ladders and pay rules. Occupational expertise, in contrast, is estimated to play a far more important role in the earnings profiles of those in prestigious, high-paying but more competitive jobs. This is particularly true in less restricted workplaces, where there is no union representation or seniority-pay scales, like in the non-union sector. Overall, the findings of this study provide some rather useful insights into the patterns that govern individuals' wage growth and are informative about individuals' employability and job mobility that could prove to be helpful to policy makers on unemployment and wage inequality issues.

Chapter 1

1 Introduction

The contribution of human capital analysis to the understanding of economic and social behaviour has long been acknowledged and become a popular area of study in labour economics. The process by which individuals develop their skills through formal education and on the job are fundamental to an understanding not only of why earnings differ but to an understanding of a country's economic and social development as well. Although the concept of human capital goes back many centuries it was only thirty years ago that the systematic economic analysis of human capital formation and its implications for labour economics initiated. Despite the volume of studies in this area, human capital theory still preserves its importance and appeal in a continuous evolving labour market to both researchers and policy makers. The wage, tenure relationship is a core element of the dynamic structure of wages that can provide to the researcher a helpful insight into how earnings evolve over one's career. The analysis of this relationship can also be informative on job mobility issues and issues related to the flexibility of the labour market, when examined from the transferability of skills, across jobs, point of view. The understanding of the wage-tenure profiles is therefore central in interpreting labour market behaviour and assessing the potential outcome of policies designed to affect this behaviour. This thesis is an empirical study of the British labour market and examines the significance of accumulated employer-tenure on individuals' earnings profiles. Using data drawn from the first eight waves of the British Household Panel Survey (1991-1998) the author examines the kind of skills individuals acquire in work and their contribution to wage determination in the 1990s. Most of the existing studies in the literature on the returns to tenure mainly focus on the methodological issues related to the potential unobserved heterogeneity bias in the estimates of interest, neglecting some other important aspects of the topic.

Obtaining a single estimate of the tenure effect may probably mask considerable heterogeneity across the workforce. Is the contribution of employer specific skills and seniority on earnings the same between individuals located at the top and bottom of the wage distribution? If not, then a more detailed examination can provide to the researcher a more complete picture on the tenure effect that may have useful implications concerning wage growth and earnings inequality. For example, if the estimates on employer-tenure effect are larger in magnitude for those individuals located at the lower part of the wage distribution, compared to those at the upper part of the distribution, then one may argue that accumulated employer-specific skills and job seniority can reduce earnings inequality. Furthermore, most of the researchers in this area distinguish accumulated human capital in work into a firm specific and a general labour market element. However, in a modern labour market environment with all the technological advancements that take place and the increasing employers' requirements and expectations this framework may be rather simplistic and even misleading. The question that is interesting to address here is whether there is any industry or occupation specific dimension in the accumulated skills in work and their significance on earnings profiles. Is industry or occupational expertise an important determinant of wages? And, are there particular industry or occupation choices that are more rewarding than others? Finally, I believe it is also helpful to examine these issues within a framework where one can incorporate the changing features of union representation and its restricted role since the 1970s. Trade unions are traditionally associated with egalitarian pay policies and job security. How has their role evolved through the, relatively recent, restrictive legislations and the declining union membership? Furthermore, are there differences in the tenure-earnings profiles between union and non-union sector? These are the main issues that I attempt to shed some light on in this thesis. However, in order to assess the importance and implications that the findings may have, it is necessary to have a broad and accurate view of the current labour market and its features.

One of the public's perceptions of the British labour market in the 1990s is that the notion of the *'job for life'* has ceased to exist. People believe that job mobility has become more frequent while work has become less stable and secure, composing a picture of a high-turnover labour market. The early evidence on job duration and labour turnover (Gregg and Wadsworth, 1995; Burgess and Rees, 1996) is in a way conflicting. Gregg and Wadsworth (1995) using the British Labour Force Survey (LFS) for the period 1975-1993 argue that job tenure has fallen in the 1990s. According to the authors, median job tenure has fallen around 20 per cent since 1975, although this aggregate figure disguises larger falls in average male tenure and a rise in female employment durations for the same period. Antithetically, Burgess and Rees (1996) using a different data source, the General Household Survey (GHS) for a similar period (1975-1992), suggest that average job tenure has not fallen much in Britain.

A more recent examination by Gregg and Wadsworth (1999b) of job duration for the period 1975-1998 tries to explain and bridge these discrepancies in the referred above studies. Despite the public belief, job tenure on average has remained fairly stable since 1975. Nevertheless, this stability at the national level conceals a contrasting reality across gender. Job stability is falling for nearly three-quarters of the workforce, men and women without dependent children. For men, job tenure rose by 10 per cent up to 1985 and fell by 5 per cent thereafter, to an average job tenure of 6 years and 10 months in 1995 based on GHS (6 years and 6 months based on LFS). This decline continued in the coming years resulting in an average job duration of 5 years and 9 months in 1998 (LFS). Job tenure patterns over time for women without dependent children are similar to those of men. At the aggregate level though rising job stability amongst women with dependent children has largely offset these changes. For this part of the labour force, job tenure has risen by around 25 per cent over the period 1975-1995, with most of this increase taking place in the period between 1985 and 1995, probably due to the increased provision and use of maternity leave. Although these reported changes in the average job duration are quite modest for most of the labour force, two groups that appear to be rather vulnerable are young people below the age of 25 and men aged 50 and over. For the former, median tenure has declined by 30 per cent between 1975 and 1985, followed by a further 7 per cent decrease in the years to 1995, mainly due to the increased share of short-term jobs. It is older men though those who experienced the largest fall in tenure, down from 15 years and 3 months to 13 years and 8 months between 1975 and 1995, primary due to a fall in the share of long-term jobs.

The main reasoning behind the declining job stability is the fact that there are fewer long-term and more short-term jobs available than before. Using information in the LFS from 1992 to 1997 (spring), Gregg and Wadsworth (1999b) report that a typical new job lasts fifteen months, while the average length of a job in progress is around five and a half years. Of those new jobs, only one-fifth last five years, whereas only a third of the jobs that have lasted five years will break up within the next five years. Although full-time permanent posts have almost certainly not become less stable, the labour market now contains more unstable forms of employment than ever before (Gregg and Wadsworth, 1995, 1996). Those individuals in part-time or temporary jobs and self-employment face far shorter job durations and so greater job instability compared to those in full-time jobs.

Despite the declining job stability for most parts of the labour force and the increasing share of short-term jobs, there appear to be signs of improvement in the British labour market since the recent recession of 1993. Unemployment rate is often regarded as a measure of how healthy the state of the labour market is. If indeed unemployment is a good indicator of performance, then one may argue that the condition of the British labour market in the late 1990s has improved, with an unemployment rate below 6 per cent (the lowest for twenty years) and one of the highest employment-to-population ratios among developed nations. However, these appealing figures mask the fact that worklessness is increasingly concentrated on selected individuals, households, socio-economic groups and geographical areas. In particular, although most people experience brief unemployment spells, for the minority who do not leave quickly unemployment becomes prolonged. The more unemployment an individual faces then, the greater the extent of future unemployment that person faces (Arulampalam *et al.*, 2000; Dickens *et al.*, 2000; Gregg, 2001). Furthermore, even though regional unemployment differentials are lower now than they have been for many years (Jackman and Savouri, 1999), there is much greater variation in unemployment performance within regions than between regions. Indeed, at finer levels of regional disaggregation the dispersion becomes greater. The worst geographical concentrations of joblessness are in council-housing estates, where typical unemployment rates are 25 per cent or above.

Unemployment also appears to affect future earnings. Arulampalam (2001), using the British Household Panel Survey 1991-1997, finds that there is a wage penalty attached to an unemployment spell on re-entry jobs that takes an inverted U-shape. In particular, an individual coming from unemployment will earn 6 per cent less in the first year of re-entry compared to what he would have earned in the absence of unemployment. This wage penalty increases over the next three years within the same employment to about 14 per cent before declining to around 11 per cent. The author does not find though any evidence that the length of the interruption itself has any additional significant effects. The estimates imply that it is the incidence of unemployment that has the wage scarring effect, and especially the first spell of joblessness in the case of multiple interruptions. Gregg and Jukes (2001) provide further evidence on the wage penalty associated with joblessness, based on a different British data set[1]. According to the authors, the impact of unemployment occurs in two parts, relating to both incidence and duration. In particular, they find that unemployment incidence gives rise to an earnings penalty on re-engagement of 10 per cent in the first year. However, this is largely temporary and is expected to have a long run or permanent effect estimated at 1.9 per cent. On the other hand, the impact of duration is estimated to be permanent, with a six months spell adding a further 5.1 per cent penalty that rises to 11.1 per cent for those who had been out of work for a year.

Overall though one may argue that despite the concentration of unemployment on particular groups of individuals and the wage penalties associated with joblessness, the aggregate unemployment rate has fallen to levels similar to those observed in the late 1970s, around 5 per cent. Yet, although both men and women have benefited equally during the current recovery, since 1993, employment rates for women are higher than any time since the war, while male employment rates are still well below the levels in the 1970s (Dickens *et al.*, 2000). What is hidden behind this is the worryingly increasing economic inactivity among the male labour force (Campbell, 1999; Gregg and Wadsworth, 1995, 1999a; Dickens *et al.*, 2000). Labour market inactivity is considered to be an unpleasant and undesired situation

---

1 The NESPD-JUVOS data set, which links the New Earnings Survey Panel Dataset (NESPD) with the Joint Unemployment and Vacancies Operating System (JUVOS).

for both the individual and the society, usually resulting to the atrophy of acquired job skills and human capital and commonly associated with deprivation and social stigma. Men have dropped out of the labour force in unprecedented numbers. In the mid 1970s there were around 400,000 economically inactive men (excluding those in full-time education), by the year 1990 this figure has increased to some 1.5 million and in 1998, it further rose to around 2.3 million, which is more than 13 per cent of the potential workforce. In contrast, the equivalent inactivity rate for women has fallen steeply from 37 per cent in 1975 to 27 per cent in 1998, an almost equal and opposite swing compared with men. Most of this rising labour force participation is concentrated amongst more highly qualified women aged between 25 and 49. So, while the numbers of economically inactive have not changed much in the last two decades, the composition of inactivity has altered radically. The proportion of the inactive that are male has risen five-fold since 1975, from 7 per cent to 35 per cent.

Economic inactivity amongst men is highly correlated with labour market conditions, being concentrated amongst older, less skilled people and amongst those living in local authority housing. While male inactivity has risen for all age groups, the most dramatic increase has been amongst those over-50s. For this group of the male workforce inactivity figures have risen from 7 per cent in 1975 to 28 per cent in 1998. In addition, more than 30 per cent of men with no formal qualifications were outside the labour market in 1998, while less than 8 per cent of men with a degree were inactive the same year. It appears that the lower the level of qualifications held, the more likely it is that a person will be economically inactive. Finally, poor labour market performance and lack of earning opportunities for men are associated with higher inactivity rates. Therefore, areas with high male unemployment, typically urban areas, have higher inactivity rates. Growing male inactivity appears to be a serious and pressing issue in the British labour market.

The poverty and social exclusion associated with inactivity necessitates policy-makers' attention in order to reconnect these people with the labour market and prevent others dropping out of the labour market.

Another alarming aspect of the British labour market in the 1990s is the increasing wage inequality (Machin, 1999). Wage dispersion between the rich and the poor has widened dramatically in Britain since the late 1970s, resulting to the highest wage inequality observed in this century. Inequality increased rapidly in the 1980s, followed by a slower rising wage inequality in the 1990s. Machin (1999), using the Gini coefficient, shows that hourly earnings dispersion increased by 30 per cent for men and by 27 per cent for women between 1979 and 1990. In the 1990s the Gini coefficients continued to increase for males at 1.2 per cent a year, but actually felt marginally for females between 1990 and 1996. The primary driving factor behind the increasing inequality appears to be the labour demand shifts in favour of the more educated and skilled due to skill-biased technological developments, as faster skill upgrading has occurred in more technologically advanced industries. The 1990s have also seen rapid educational upgrading. This rise in high-skilled labour supply has slowed down the increase in wage inequality in the 1990s. Apparently though, this rising supply was not enough to meet employers' need for a high-skilled workforce, so labour demand has continued to shift in favour of more educated and skilled workers. Besides the technological changes and the increased requirements for high-skilled labour supply, some of the rise in wage inequality can also be attributed to the decline of trade unions in the British labour market since the late 1970s. However, the latter has rather limited explanatory power as in both union and non-union sectors wage inequality grew over the 1980s (Goslin and Machin, 1995; Machin, 1997), although it rose faster in non-union workplaces.

Continuing on to low pay and earnings dynamics, Webb *et al.* (1996) show that the incidence of low pay, defining low pay as below two-thirds of the median for all workers in any year, has shifted from women to men and from younger to older. In 1994 females were roughly two and a half times as likely to be low paid as males, whereas in 1968 they were more than six times as likely (based on the Family Expenditure Survey, for the period 1968-1994). The rate of low pay amongst men has roughly doubled since 1975, while for women the rate in 1994 is marginally below that in 1975. Furthermore, the age composition of the low-paid male workforce has changed notably. Whilst male low pay in 1968 was predominantly amongst young men, low pay for those aged over 25 rose sharper than those young men: the number of low-paid men between 25 and 49 roughly quadrupled over the period 1968-1994. The age composition amongst females remained fairly stable over the same period. In addition, low pay is more prevalent amongst casual workers, those in small firms, those in non-union firms, ethnic minorities and less-skilled manual workers (Stewart, 1999).

Low pay incidence also appears to be quite persistent (Stewart, 1999; Stewart and Swaffield, 1999). The probability of being low paid in one year is much higher if you were low paid in the previous year. Furthermore, the longer one remains low paid, the lower the probability of their moving up the wage distribution and out of low pay. Even for those above the low pay threshold, prior low pay experience increases the probability of returning to it. Dickens (2000) also in a study on the extent of earnings mobility in Britain shows that there is considerable immobility within the earnings distribution from one year to the next. In addition to persistence in low pay, it is evident as well that the low paid are much more likely to leave employment than those in the higher part of the wage distribution. Apparently (Stewart, 1999), there is a "*low pay - no pay*" cycle, where "*the low paid are more likely to be out of work in the future; those out of work are more likely to be low* *paid on re-entry; and are even more likely to be so if they had been low paid prior to being out of work*" (pp. 239). After all, "*low-paid jobs are more likely to act as blind alleys than as stepping-stones to positions higher up the pay distribution*" (pp. 241).

In conclusion, the British labour market in the 1990s appears to be characterised by the operation of a primary and a secondary sector. The primary sector is represented by well-educated, prime-age workers located at the mid and higher end of the wage distribution who enjoy job stability and security. In contrast, the secondary sector is characterised by less skilled, young, and old in atypical employment with high labour turnover. These individuals are usually concentrated in low paid jobs that tend to be far more unstable and insecure. For them, the penalties attached to job loss and jobless duration are quite severe and their re-entry wages are rather reduced. These features, describing those at the bottom, compose a picture of a disheartening and discouraging way of life, with limited chances of upward progression. The British labour market seems that it is becoming an ossified, inflexible environment, where early development and progress are fundamental ingredients to an individual's life chances. Therefore, it is important to provide these, more vulnerable, people the appropriate training and to match them in more stable jobs, where they are most suited in order for them to acquire all the necessary skills on the job. There are of course some programmes in place, like the New Deal that involves an element of education and training. Unfortunately, the scale of intervention is modest and skill development under this programme seems to be limited (Dickens *et al.*, 2000). "*If these policies are to be as successful as education in improving life chances, large investments are needed to have an impact on the earnings of marginalised groups*" (pp. 11). The current developments in the British labour market underline the importance and usefulness of examining the kind of skills that people accumulate over the years in work and their contribution on earnings. Understanding what matters most in wage determination can be quite helpful to policy makers in the evaluation of existing labour market programmes and the outline of future directions that attention should be focused on.

To briefly summarise the structure and content of the thesis, in *Chapter 2* I present an analysis on the returns to employer-tenure. First, a summary of the data used throughout the thesis is provided at the beginning of this chapter along some descriptive summary statistics of the data sample. A standard Mincer wage equation model describes the main empirical framework, where accumulated human capital in work is divided into employer specific and general labour market skills. Here I address the issue of endogeneity bias in the estimates of interest and employ several techniques suggested in the literature to assess the robustness of my findings. In the second part of this chapter, I question the assumption of a homogeneous tenure effect across the workforce and explore the contribution of tenure at various points of the wage distribution.

In *Chapter 3*, I challenge the conventional division of accumulated human capital into employer specific and general labour market skills and examine the possibility of industry and occupational specificity. The issue of potential endogeneity bias in OLS estimates on earnings equations is also address here and I present alternative estimates based on panel estimators. Furthermore, I explore whether the estimated industry and occupational experience effect are driven by particular industry or occupation choices.

The third substantive chapter, *Chapter 4*, explores how institutional arrangements influence the estimated human capital premia. Particularly, the aim here is to distinguish the different paths that seniority-earnings profiles follow depending on whether there is union representation at the workplace and/or whether formal wage scale rules are adopted. Trade unions are traditionally associated with the standardisation of pay-setting procedures, the enforcement of objectives rules concerning promotions and wages in the workplace. Within this framework, I set two propositions related to seniority profiles and union representation. In particular, I argue that in the union sector it is expected that job seniority and skills specificity will be an important determinant of wages, while in the less structured non-union sector true productivity, proxied by the more competitive accumulated skills and professional expertise, will have a key role on earnings profiles.

The main findings of the thesis are summarised in the final chapter, ***Chapter 5***. Here I bring together the evidence presented in the previous three empirical chapters and provide an overview of the results. Also, I outline the implications my findings have for the British labour market and discuss policy issues raised by the analysis throughout the thesis.

Chapter 2

2 The Effect of Employer-Tenure on Wage Growth

2.1 Introduction

The contribution of employer-tenure to wage determination is a popular subject of research in labour economics and not without reason. The understanding of the dynamic structure of wages is central in interpreting labour market behaviour and the potential impact of policies designed to affect this behaviour. The wage, tenure and experience relationship is a core element of this structure, and hence garners considerable attention. The extent to which wages rise with tenure has many useful implications concerning issues of government policy. First it gives an insight into the evolution of life-cycle earnings, which is important in a number of fields (pensions, labour supply, savings, etc.). Second it is informative on job mobility issues. Identifying the characteristics of job mobility can be very helpful in the evaluation of labour market programs. In particular, many European governments became interested in such programs as a remedy for long term unemployment. Governments now give a high priority to policies thought to stimulate training, either through direct interventions and subsidies of company training or, through support for a '*training market*' via loan provision, dissemination of information about good practice and others measures. Therefore, wage growth estimates on the job as well as the extent to which the acquired human capital is transferable between jobs is a key element in the evaluation of the potential effects such programs may have. Furthermore, the examination of how flexible, in terms of transferability of skills, the labour market is and the extent to which the earnings power of individuals is tied to specific jobs can be very useful when thinking about the efficient allocation of human resources, individual's business cycle decisions, the characteristics and growth of wage profiles, as well as individual's employability and productivity issues.

As data on seniority and large scale panel data sets became available in the 1970's, several researchers (Mincer and Jovanovic, 1981, among others) concluded that there is a large return to seniority based on the fact that there is a strong positive relationship between tenure and wage rates in cross sectional or pooled cross section-time series data. A growing theoretical literature has taken the evidence of a strong wage-tenure profile at face value and sought to provide an explanation for the relationship. The most prominent explanation is the theory of specific human capital, according to which the growth of wages with tenure is attributed to the accumulation of firm-specific skills (Oi, 1962; Becker, 1962, 1964, 1975; Parsons, 1972; Mincer, 1974; and Hashimoto, 1980). Individuals working in their jobs acquire a range of skills over the years, which can be either the result of on-the-job training or, the outcome of seminars or, training courses sponsored by their employer. These skills can be divided into two main categories: (a) general skills and (b) employer/firm specific skills. The latter skills refer to knowledge and abilities obtained on the job that are employer-specific, thus appreciated only by the current employer. Within this framework, the positive wages-tenure relationship is actually the reward for the valuable acquired firm-specific human capital. More recently, other models have been presented, such as a supervision model of wage growth (Lazear, 1981) where the prospect of higher pay in the future deters shirking and induces effort in the present, a model for wage growth based on an insurance motive (Freeman, 1977; and Harris and Holmstrom, 1982) and an adverse selection model of wage growth (Nickell, 1976; Salop and Salop, 1976; and Guasch and Weiss, 1982).

However, several economists have noted that unobserved heterogeneity across individuals and across job matches may produce inconsistent estimates of the effect of tenure on wages and turnover. Since tenure is a simple function of job changing decisions, attention has to be given to the effect of individuals' and jobs' characteristics on quits and layoff decisions. Recent evidence indicates that many job-changing decisions are the outcome of a career process by which workers are sorted into more durable and productive jobs. High-wage jobs tend to survive, which means that people with long tenures earn higher wages. In addition, it is possible that more productive or able workers change jobs less often, for which there is also empirical support. Several papers in the mid 1980's, with Altonji and Shakotko (1987) (hereafter AS) and Abraham and Farber (1987a) (hereafter AF), as widely cited examples, challenge the previous findings, arguing that returns to seniority are relatively small and moving the literature to a new consensus.

In this chapter, using data from the first eight waves of the British Household Panel Survey, I examine the contribution of employer-tenure to wage growth in the British labour market. In *Section 2.2*, I present an extensive analysis of the wages-tenure profiles literature, giving particular attention to the three probably most influential studies in this area: AS (1987), AF (1987a) and Topel (1991). Despite the extensive research on the seniority effect, predominantly on US data, there is still controversy in the findings among the studies. One of the purposes of the literature review below, is to provide to the reader a comprehensive discussion of the methodological issues raised, primarily due to potential heterogeneity bias in the estimates of interest, and to examine the implications and candidate interpretations that these, some time contradicting, results may have.

The literature review is followed by the empirical analysis in *Section 2.4*, where I explore the role of employer-tenure in the wage determination process. In particular along OLS estimates, which serve as a benchmark point in my discussion. I replicate AS and Topel's methodology and assess the findings from these different estimators. Furthermore, I utilise the panel element of my sample and employ panel estimators (both random effects and fixed effects) as an alternative way of correcting the heterogeneity bias in the wage equation model considered. Finally, in the last part of this section I test the sensitivity of my findings to outliers in the reported wages, using quantile regressions. The results obtained from all the estimators described here are tested against various specifications in order to assess their robustness and to further discuss the implications that their choice as a preferred estimator may have on the examination of tenure effect.

The quantile regression estimator is further utilised in ***Section 2.5***, where I calculate a group of estimates of the contribution of tenure, corresponding to different points of the wage distribution. This is the first time, at least for a British study, to the author's knowledge that such a technique is used for the examination of tenure effects. The advantage of this estimator is that it does not restrict the researcher to estimates '*on the average*', on the contrary it provides estimates over the whole spectrum of the wage distribution. In fact, what I attempt in this section is to challenge the conventional assumption of a homogeneous tenure effect and to present an alternative way that allows employer-tenure to have a varying (both in magnitude and significance) role at different quantiles of the wage distribution. This approach is rather insightful in the examination of the true contribution of tenure and raises several key issues of interest, previously '*hidden*' behind average treatment effects. Finally in ***Section 2.6***, I conclude my analysis with the main findings on tenure-wage profiles and discuss implications and directions for further research.

2.2 Wage Equations and Heterogeneity Bias (Literature Review)

A standard Mincer (1974) wage equation model, used by many economists, including AF (1987a), AS (1987) and Topel (1991), is given by:

$$W_{ijt} = \beta_{0t} + \beta_{1t}E_{ijt} + \beta_{2t}T_{ijt} + \varepsilon_{ijt} \tag{2.1}$$

where W_{ijt} is the log wage of person i in job j in period t, E_{ijt} is total labour market experience, and T_{ijt} is tenure with the employer. The equation (2.1), for illustration reasons, abstracts from a set of control variables, and from nonlinear terms in experience and tenure. The error term can be decomposed into three components,

$$\varepsilon_{ijt} = \mu_i + \varphi_{ij} + \eta_{ijt} \tag{2.2}$$

where μ_i is a fixed, time and job invariant, individual specific error component, φ_{ij} is a fixed, time invariant, job match specific error component, and η_{ijt} is the transitory error component that accounts for marketwide random shocks as well as measurement errors. The individual effect μ_i represents the individual's unobserved ability, while the job-match effect φ_{ij} captures the quality of the employment relationship stemming from search activity. Individuals with high unobserved ability (high μ_i) most likely experience lengthy and less interrupted employment spells, while better matches, choices of job, (high φ_{ij}) are more likely to occur to individuals with more experience, as the result of human capital and lengthy search, and are expected to last longer (i.e. lower labour turnover).

The key parameters of interest are β_1 and β_2, where β_1 represents the return on general human capital (training and the like) that accumulates with experience, while β_2 represents the return on seniority and accumulated job-specific capital that would be lost if a job were to end. The parameter β_0 is an economy wide trend in real wages. Many researchers that use OLS to estimate these parameters, consistently find that seniority has a significant, large and positive effect on earnings. As an example of the size of this effect, AS (1987) and Topel (1991) reported that ten years of seniority raises the log wage by roughly 30 per cent.

However it is argued that using OLS to estimate β_1 and β_2 may be inconsistent, since employer-tenure and experience are likely to be correlated with the unobserved individual and job match heterogeneity. In order to present the biases that arise from unobserved individual and match heterogeneity in a formal way, we can use the auxiliary regressions between the unobserved components and experience and tenure, given by:

$$\varphi_{ij} = b_1 E_{ijt} + b_2 T_{ijt} + \xi_{ijt} \tag{2.3}$$

$$\mu_i = c_1 E_{ijt} + c_2 T_{ijt} + \omega_{ijt} \tag{2.4}$$

In equation (2.3) matching models and conventional search models imply that job shopping over a career will induce a positive correlation between E_{ijt} and ϕ_{ij} $(b_1 > 0)$. In addition workers will be less likely to quit high wage jobs than low wage jobs. Furthermore, if firms share in the returns to a good match, ϕ_{ij} will be negatively correlated with the layoff probability, suggesting a positive correlation between tenure and ϕ_{ij} $(b_2 > 0)$. Topel though argues that the sign of b_2 is ambiguous since the selection induced by voluntary job changes will lead low tenure values to be associated with large values of ϕ_{ij} and b_2 may be negative. In equation (2.4) tenure will be positively correlated with μ_i in the likely event that individuals with low productivity (low μ_i) have high quit and layoff propensities

$(c_2 > 0)$. Individual heterogeneity associated with μ_i will bias OLS estimates of the wage-tenure profile upwards. Finally c_1 is expected to be negative.

Summarising, the biases in the OLS estimators of β_1 and β_2 are:

$$\beta_{1(OLS)} - \beta_1 = b_1 + c_1 \tag{2.5}$$

$$\beta_{2(OLS)} - \beta_2 = b_2 + c_2 \tag{2.6}$$

As it can be seen from the analysis above, neither bias can be signed. The bias in experience is ambiguous because the job match (b_1) and individual heterogeneity (c_1) terms are of opposite signs. Similarly, the bias in tenure is ambiguous since the match heterogeneity (b_2) may be either positive or negative. However, if c_2 is large and positive and b_2 is either positive or small and negative, then the net bias in $\beta_{2(OLS)}$ will be positive, and the estimated effect of seniority on wages will be overstated in OLS wage regressions.

2.2.1 Altonji and Shakotko's Estimator

AS (1987) address the problems of individual and job match heterogeneity in the wage equation using an instrumental variables estimator, IV_1. The principal instrumental variables for the tenure variable is the deviation of the tenure variable from its mean for the sample observations on a given job match (DT_{ijt}). By construction this instrument is uncorrelated with both the individual specific error component of the wage equation (μ_i) and the permanent job match component (φ_{ij}), which are assumed to be time-invariant. If the instrument is also uncorrelated with the transitory error component (η_{ijt}), then this variable (DT_{ijt}) is a valid instrument. AS use DT_{ijt}, X_{ijt} and t as instruments (IV_1 estimator).

The data set used in AS's analysis is based upon the 1968-1981 waves of the PSID and is restricted to a sample of white male heads of households aged between 18 and 60. In their analysis the OLS estimates do not defer from the typical estimates obtained in cross sectional analyses of the wage equation. They find a substantial growth of wages with tenure, with much of the growth occurring in the first year on the job. In contrast, the IV_1 estimates indicate substantially smaller first year growth and a virtually flat tenure profile afterwards. According to their estimates the accumulation of the first ten years of tenure results in a wage increase of 2.7 per cent, i.e. $1/11^{th}$ of the corresponding OLS estimate. Furthermore the OLS estimates indicate that total labour market experience raises wages by 31.7 per cent during the first ten years of work and 48.2 per cent during the first 30 years, while the corresponding IV_1 estimates are 53.7 per cent and 86.6 per cent. These estimates are expected since the strong positive correlation between experience and tenure implies that the upward bias in the tenure profile, analysed above, will lead to a downward bias in the experience profile.

AS recognise that their IV_1 estimator may be biased. In particular, while the IV_1 estimator is free of bias from μ_i, the likely positive correlation between E_{ijt} and φ_{ij} leads to a positive bias in $\beta_{1(IV_1)}$ and a negative bias in $\beta_{2(IV_1)}$. The corrected IV_1 estimator can be defined as

$$B_{IV_1^*} = B_{IV_1} - B_{bias(IV_1)} \tag{2.7}$$

Using the $B_{IV_1^*}$ estimator, AS obtain 6.6 per cent as their preferred estimate of the effect of ten years of tenure. Overall, the AS instrumental variable approach on the wage equations indicates that tenure has a modest effect on wage growth, with total experience accounting for most of the growth during a career. From the analysis it is clear that heterogeneity bias is responsible for the much larger least squares estimates of the tenure profile in the literature.

2.2.2 Abraham and Farber's Estimator

AF (1987a) recognise as well the existence of bias in the OLS estimates of the wage equation deriving from the individual, job and/or match quality heterogeneity. The approach to removing the upward bias that they suggest, is to control explicitly for completed job duration in the earnings equation. According to their analysis the tenure coefficient is biased only because seniority is associated with the completed length of current job, which in turn is correlated with φ_{ij}. The method AF propose in order to control for heterogeneity is to include the expected completed tenure T_{ij}^* of each job in the standard cross-section earnings equation (2.1). Augmenting the wage equation (2.1) by adding T_{ij}^* as an explanatory variable yields

$$W_{ijt} = \beta_{0t} + \beta_1 X_{0ij} + (\beta_1 + \beta_2) T_{ijt} + \psi T_{ij}^* + \varepsilon'_{ijt} \tag{2.8}$$

AF argue that the augmented OLS approach has two important advantages. First, it provides a direct estimate of the relationship between completed job duration and earnings (ψ), which is an indicator of the importance of the relationship of individual, job and/or match heterogeneity with earnings through job duration. Second, it provides an insight for the hypothesis that better workers, jobs, or matches are associated with higher earnings throughout the job.

The sample used in their analysis, similar to the one used by AS, includes male household heads aged between 18 and 60 who participated in the PSID from 1968 through 1981, excluding observations on unionised jobs. They particularly focus their discussion on two occupational subgroups. A subset of white-collar occupations including nonunion professional, technical and managerial employees, and a subset of nonunion blue-collar employees. Their analysis is based on three different approaches, (a) a standard OLS earnings that neither instruments for seniority nor includes completed job duration as a regressor, (b) an IV approach, using pre-job experience, the square of pre-job experience, and the residual from the regression of seniority on completed job duration as instruments for total experience, the square of total experience and seniority and (c) an augmented OLS approach, described above.

Their standard OLS estimates suggest that there are significant sizable returns to both general labour market experience and employer seniority for workers in both occupational groups. The estimated return to seniority ranges from 1 to 1.5 per cent per year. On the other hand, while their IV approach has relatively little effect on the estimated return to general labour market experience, the estimated net return to seniority falls substantially. For the white-collar workers the return to seniority falls from 1.1 to 0.6 per cent per year, and for the blue-collar workers falls from 1.4 to 0.3 per cent per year. This suggests that most of the cross-sectional correlation between earnings and seniority, controlling for experience, reflects the influence of omitted variables. Finally the augmented OLS estimates are virtually identical to those obtained using the IV approach. What stands out from the augmented OLS estimates is that there is a very strong positive association between completed duration and earnings in both the occupational groups. Their results also confirm the finding that workers in longer jobs earn more in every year on the job than workers in shorter jobs for both the occupational groups, though it is more apparent in the case of white-collar workers.

In summary AF's results suggest that there is only a small average return to seniority in excess of the average return to general labour market experience. Furthermore, it seems that workers in long jobs earn considerably more through out their jobs than do workers in short jobs. This finding has important implications for the decisions that employers and workers make, since it affects investment in job-specific capital and the incentive for workers to remain on their job.

2.2.3 Implications and Criticism on AS and AF's Studies

Both AF (1987a) and AS (1987) suggest that the partial effect of tenure on wages is small, and that general labour market experience and job shopping account for most wage growth over a career. This conclusion has important implications for the labour market. One can argue that it means that human capital investments are mainly general rather than firm specific, so that the main component of workers' embodied skills is portable among firms. Further, in the absence of specific capital, the costs of worker displacement and unemployment are likely to be small, even for relatively senior workers since their accumulated skills are transferable across jobs. Finally, the '*independence*' of wages and job tenure questions the compensation literature that treats the timing of wages as a strategic device for affecting worker productivity.

However, tenure responses in the PSID are often inconsistent with calendar time. Brown and Light (1992) (hereafter BL) in their study identify several problems arising from this inconsistency. First, the failure to use internally consistent tenure sequences can lead to misleading conclusions about the slope of wage-tenure profiles. Second, the inclusion of jobs that contain unusually inconsistent tenure responses can alter the results in certain applications, which particularly true for the 1968-1974 PSID data, the sample used by AS and AF. Third, the reliability of estimates that require precise information about job changes may be seriously reduced when error-ridden tenure data are used to identify job changes. Finally, it is quite likely that estimates of job changes from tenure responses are overstated.

BL suggest several rules for partitioning PSID data into jobs and they examined the effect that these different kinds of partition have on estimates from commonly used wage and mobility models. They estimate a simple cross-sectional wage equation, a fixed-effect model of within-job wage growth, a model of within-and between-job wage growth and a simple logit model for job separations. In all these models, their findings show that the estimates are heavily dependent on the choice of partition. Furthermore they examine the sensitivity of the estimates when the sample is limited to reliable observations, deleting all the unreliable observations. BL estimate a fixed-effect model and find that while the full sample indicates no important role for job tenure in determining the slope of within-job wages profiles, the reliable subsample indicates that the role of tenure is no less important than that of experience. According to the authors, the choice of whether or not to include these observations proves to be more important than the choice of partition. In conclusion, BL's study seriously questions the validity of the AS and AF's findings, which are based on PSID data from the years 1968-1981.

2.2.4 Topel's Estimator

Topel (1991) in his study practically re-establishes that the accumulation of specific human capital is an important ingredient of the typical employment relationship and of life cycle earnings and productivity as well. His analysis is based on a two-stage estimation procedure. The idea is that within-job wage growth combines the return to general and job-specific experience, since both of them increase identically within a job. Therefore, the first stage estimates the determinants of wage growth without distinguishing separate returns to general market experience and job-specific seniority. The second stage is actually a cross-sectional comparison of the wages of workers who started new jobs at different points in their careers. In this stage an upper bound on the returns to general experience is estimated, which, combined with the estimates in the first stage, can be translated as a lower bound on the returns to tenure in the typical employment relationship.

Topel in his analysis de-trends the data using a real wage index constructed from CPS cross sections in an early draft of Murphy and Welsh (1992)[2]. The first step is given by applying OLS to a within job wage growth equation for stayers

$$W_{ijt} - W_{ijt-1} - \hat{\beta}_0 = \beta + \varepsilon_{ijt} - \varepsilon_{ijt-1} + \beta_0 - \hat{\beta}_0 \tag{2.9}$$

where $\beta = \beta_1 + \beta_2$. Since current experience can be written as the sum of the initial experience on the job (E_{ij0}) and tenure (T_{ijt}), the second step of Topel's estimation is given by

$$W_{ijt} - \hat{\beta}_0 t - \hat{\beta} T_{ijt} = \beta_1 E_{ij0} + e_{ijt} \tag{2.10}$$

where $e_{ijt} = \varepsilon_{ijt} + t(\beta_0 - \hat{\beta}_0) + T_{ijt}(\beta - \hat{\beta})$ and $\hat{\beta}$ is the OLS estimate from (2.9). Finally, the linear tenure slope (β_2) is given by $\hat{\beta} - \hat{\beta}_1$.

Topel recognises that his estimates may be correlated since both μ_i and φ_{ij} are included in e_{ijt}, and both may be correlated with E_{ij0}. Particularly, he notes that

[2] This is similar to regressing the Murphy-Welsh index on a time trend using the sample composition to weight the various years, and then using the coefficient estimate $\hat{\beta}_0$ to de-trend the data.

the job matching produces a downward bias in the estimator of β_2. According to the author though, the downward bias is going to be larger for the AS's IV_1 estimator than his estimator provided that $b_1 + b_2$ is positive.

The sample used in Topel's analysis is from the PSID data for the years 1968-1983. The sample is restricted to white males between the ages of 18 and 60 inclusive, who were not self-employed, employed in agriculture, or employed by the government. The wage data refer to (log) average hourly earnings in calendar years 1967-1982. In contrast to AS and AF, Topel takes both the wage and the tenure and the union status measures from the year t survey. In addition he excludes observations of tenure duration less than one year $(T_{ijt} < 1)$ because wages refer to average hourly wages in the year preceding the survey.

According to Topel's findings the estimated value of β_1 is about 7 per cent and the estimated value of β_2 is 5.45 per cent. In other words, in the first year of the typical new job, the real wage rises by over 5 per cent because of the accumulation of job-specific experience alone. Furthermore his estimates suggest a large return to seniority. In particular, ten years of job seniority increase the log wage of the typical worker by 28 per cent, relative to alternatives, which is substantially larger than AS and AF's estimates. He suggests that the estimated returns to seniority represent the reduction in earning capacity that an individual would suffer if his job ends for exogenous reasons. However workers may bounce back from these losses quite rapidly since relative wage growth is most rapid at the beginning of new jobs. Thus initial wage losses may vastly overstate changes in lifetime wealth caused by a job termination.

In addition Topel explores the effect of several biases on his estimates. First, he finds that the downward bias in the two-step estimator of the return to seniority (β_2) is solely due to improvement in match quality with total labour market experience. Further, he examines the possibility of selection bias in wage growth and ability bias in the returns to job tenure. However, in neither of the cases does he find that these sources of bias can account for the substantial returns to seniority.

Topel also estimates the returns to job seniority among different occupational groups, professional and service, craftsmen, operatives and laborers. In the case of craftsmen, operatives and laborers he treates union and nonunion workers separately. His estimates imply that there are only minor differences across groups, with the only difference worth noting among unionised workers where there is substantially smaller variance in wage changes. Thus his main finding is that estimated returns to tenure are quite similar across broad occupational categories. However he makes a distinction between the returns to seniority for union workers when measured relative to another union job and when measured relative to the nonunion alternative. The estimated returns in the former will be similar to those in other sectors, while the estimated returns in the latter will be both larger and rising. According to Topel this will be true since the losses suffered by a union worker, whose job were to end and was forced to seek employment in the nonunion sector, combine both the union seniority effect and the union wage premium.

Topel in his study made a serious effort to explain the discrepancy between his findings and those of AS and AF. Although AS and AF use the same data (PSID) for their analysis they find quite different results than Topel, according to their findings the true returns to job seniority are minor. Topel re-examining the AS's approach concludes that their estimates are substantially biased down. He highlights three reasons accounting for this downward bias: (a) the instrumental variable procedure used by AS produces a greater upward bias in the return to experience and so, a greater downward bias in the return to tenure, (b) there is serious measurement error in recorded job tenure which precludes reasonable estimates of the parameters of wage growth to be derived from the uncorrected data, and (c) the treatment of the time trend as exogenous causes an additional downward bias in estimated returns to seniority. Further, Topel argues that the difference between his estimates and those of AF arises solely because AF used an inappropriate methodology, which yields an inconsistent estimator of $\beta_1 + \beta_2$. In conclusion, Topel's analysis advocates a very strong connection between job seniority and wages in the typical employment relationship, other things constant, ten years of job seniority are expected to raise the wage of a typical worker by over 25 per cent.

2.2.5 A Re-Estimation of the Approaches to the Wage-Tenure Profile

Many researchers investigate further the discrepancies in the findings between AS, AF and Topel on the seniority-earnings profiles. Williams (1991) re-examines the contribution of employer-tenure and general labour market experience in the wage determination process and attempts to assess the conflicting results that AS (1987) and Topel (1991) present in their studies. The data used in the analysis are from the Seattle and Denver Income Maintenance Experiments (SIME/DIME). These data have the advantage that they provide improved tenure information since more low tenure jobs and wage changes at low levels of tenure are recorded, contrary to PSID that both the AS and Topel used in their papers, which does not provide any information regarding multiple wage or job changes in the previous year.

The author suggests two approaches in order to control for unobserved heterogeneity in the estimated wage equation model. The first method is based on a job fixed effects estimator. Under the assumption of individual and job characteristics, differencing across individuals and jobs will remove the unobserved components from the estimated model. The main drawback of this method is that since tenure, experience and time increase by the same amount between wage arrivals, the linear term of tenure and experience and time cannot be identified. However, a consistent estimate of their sum is available and can be interpreted as the overall effect of the passage of time on wages. The alternative is an instrumental variable estimator, based on the AS IV, where tenure is instrumented by its deviation from the mean job tenure. In addition, the author presents estimates on an IV model where general experience is instrumented as well by substituting current experience with the experience level at the start of the job, similar to what Topel (1991) suggests. Nevertheless, the latter model is still an incomplete solution as both current and initial experience are likely to be correlated with unobserved heterogeneity. The findings from the job fixed effects estimator, despite the inability to separately derive the tenure and experience effect, suggest that OLS overstates the wage growth due to tenure and experience. Furthermore, the two instrumental procedures indicate a much flatter slope to the wage-tenure profile than least squares estimates. The calculated two-year tenure effect is between 5 and 6 per cent in the IV models and more than double (14 per cent) when heterogeneity bias is not corrected. The estimates on experience are fairly similar to OLS, with a derived experience effect of 15 years above 30 per cent.

Overall, the results imply that AS's findings of a moderate tenure effect, confined to the first several years on the job, are more likely to be true than Topel's tenure large wage gains. Longer tenures increase wages only for the first two years of employment with additional years having little effect. Accumulated general labour market experience, on the other hand, raises wages substantially over the years.

Altonji and Williams (1997) (hereafter AW) provide new evidence on the returns to tenure using data similar to that used by AF (1987a), AS (1987), and Topel (1991) as well as a new PSID sample for the years 1983-1991. In their study they replicate Topel's sample in order to examine the role of the treatment of secular trends, the timing of the tenure and wage data, functional form, the measures of tenure, differences in the estimators and the samples used.

Topel in his analysis argues against the use of a time trend (*t*) that both AS and AF used in their models, for two reasons. First, *t* is expected to be correlated with both φ_{ij} and μ_i. AW recognise that *t* may be positively correlated with φ_{ij}, however the covariance between these two will not lead to bias in the tenure and experience coefficients of the OLS and IV_1 estimators. In addition, they suggest that in the case of correlation between *t* and μ_i, the problem can be solved by treating time as endogenous and using the deviation of *t* from its mean for person *i*, as an instrument for time. Their findings show that the secular trend in wages in Topel's sample is larger than the trend in the CPS based wage index used by Topel to control for economy wide wage growth. Considering the consequences of using the wrong trend, AW document that there is no effect on OLS, but it causes a substantial difference in the IV_1 estimator and it has some effect on the Topel estimator.

In the PSID, although information on employer-tenure, union status and other job specific variables refer to the survey date, the wage measure is annual earnings divided by annual hours in the previous calendar year. AS and AF in their analysis use the wage measure from the survey in year *t* and tenure and union status measures from the survey *t-1*, while Topel takes both the wage and the tenure and union status measures from the year t survey, and excludes observations with measured tenure less than one year. AW find that Topel's choice of dating leads to bias, in particular the use of the period *t-1* wage with period t tenure leads to a large upward bias in Topel's results for both the IV_1 and two-step estimator.

In addition, AW argue that although AS and Topel used different functional forms, the estimates are not sensitive to the functional form used, regardless of whether the observations with tenure less than one are included. The functional form assumptions seem to explain only little of the differences in the results of the two studies. On what it concerns measurement errors in the AS tenure measure, AW support AS' views that although measurement error is important, it has little effect on their substantive conclusions. Finally AW suggest that both the IV_1 and Topel estimators are biased down by match heterogeneity, and the Topel estimator is biased up by individual heterogeneity. Their evidence showes that the downward bias in the Topel estimator from job match heterogeneity is more than offset by upward bias from individual heterogeneity. Yet, the difference between the AS' estimator and the Topel estimator is minor compared to the difference between these estimators and OLS.

Summarising AW's findings based on the comparison between AS and Topel's estimators, their main conclusion is that the returns to tenure are modest and much closer to the estimates of AS and AF than Topel's. They suggest that ten years of tenure will raise wages by around 11 per cent, which is larger than AS's preferred estimate of 6.6 per cent but far below Topel's estimate of 28 per cent and OLS estimates of 35 per cent.

Furthermore, AW criticising Topel's analysis of the AF estimator, they conclude that after one relaxes Topel's functional form assumptions and takes information on wages and tenure from the same period, the use of an estimate on job duration as a control for heterogeneity yields tenure effect between 6 and 13 per cent (1/4 and 1/2 of the OLS estimates, respectively) even if one uses the unrestricted version of AF estimator that Topel advocates. Finally, AW re-estimate the return to seniority using the PSID data for the years 1983-1991. Using the survey wage rate, they obtain a return of 4.3 per cent based on IV_1, which is probably downward biased, and a return of 12 per cent using Topel's estimator, which is probably upward biased. Their preferred returns to ten years of tenure lies between these values, around 8 and 9 per cent. Overall, AW's analysis strongly suggests that the contribution of employer-tenure on wage determination is rather limited.

AW in a later study (1998) provide further support to their previous findings, suggesting a return to job tenure larger than the one estimated by AS, but far below the OLS estimates. The starting point in their analysis is a wage equation on experience, tenure, a fixed individual specific error component, a fixed job match specific error component that changes only when the individual changes jobs, transitory error components, and other observed components. They eliminate the fixed individual effect by differencing the wage equation. Afterwards they replace the change in the job match components with their expected values conditional on a quit or layoff, tenure and prior experience, which are polynomial approximations to the true conditional expectations. This way they eliminate the bias from the fixed job match heterogeneity as well. The problem arising from this analysis is that the coefficients on linear experience and tenure in the wage level equation, and the coefficients on the linear tenure terms in the polynomial approximations are under identified by one common parameter. The authors solve this problem by imposing some inequality restrictions on the parameters of the wage growth model. They argue that if the effect of tenure on wages is substantial, then the relationship between the change in the job match component and tenure at the time of a quit (layoff) will be positive (negative). The idea behind these assumptions is that senior workers will quit only if the job match gain is sufficient to compensate for the value of lost tenure, and that jobs whose workers choose to stay in for long periods tend to be better than jobs whose workers leave quickly. In addition they assume that the match gain is zero or negative for persons who are laid off with significant amounts of seniority. The last step in their analysis is to use a Bayes estimator due to Geweke (1986) to combine prior information and sample information. Geweke's estimator combines the normal linear regression model with a prior that is the product of an uninformative distribution and an indicator function which is one when the inequality constraints is satisfied and zero otherwise.

In their empirical analysis they discuss both weighted least square estimates and formal Bayesian estimates. The sample is based upon the 1975-1987 PSID data, and restricted to white male heads of households between the ages of 18-60 inclusive. The results they present are on three different samples, based on different wage measures. AW estimate the return of seniority using least squares, AS's instrumental variable approach and Topel's estimator. According to their findings, the return of ten years job tenure ranges between 27.7 and 35.1 per cent based on OLS estimates, while in the case of AS estimator the return takes values between 10.3 and 12 per cent and in the case of Topel's estimator between 14.6 and 20.2 per cent. The OLS estimates appear to be almost three times as large as those based on AS's IV_1 estimator and almost two times as large as the estimates for Topel's estimator. Furthermore, the results based on their model, when using their preferred wage measure, suggest that ten years of tenure raises the log wage between 6 and 14 per cent. These estimates are well below the corresponding OLS results, which according to AW's analysis implies that the OLS estimation appears to substantially overstate the return to tenure. AW provide also a limited analysis of data from the National Longitudinal Survey of Youth (NLSY) for comparison. The estimates of the return to experience based on NLSY are higher than the PSID estimates, but in general the results are quite consistent with those for the PSID.

In summary, the main conclusions drawn by AW's analysis are that, first there is a large return to general labour market experience that is independent of job shopping. Second, there is an economically significant tenure effect on the log wage that is above AS's estimates, but far below AW's estimated OLS returns and also below Topel's estimates.

AW (1997, 1998) empasise that estimated returns to seniority are strongly sensitive to the type of wage information used from PSID. The estimated effect more than doubles when using the average hourly earnings, as Topel does in his study (1991), instead of self-reported hourly earnings. However, the authors fail to fully account for this sensitivity and do not give much guidance regarding which variable should be used. Lefranc (2001) in a recent study attempts to formally account for these different factors that contribute to this sensitivity of estimates to the measurement of earnings. The two explanations that he examines are that the two wage variables might refer to different definitions of earnings, therefore the observed differences in the estimates might be accounted to the differences in the scope of these two variables. In addition, even if they refer to the same definition, they might be differently affected by measurements errors that potentially can produce different results. The sensitivity analysis is performed using Topel's (1991) two-step estimation procedure, where the author compares results for different wage variables from PSID (1979-1992). On the sensitivity of the returns to tenure to the scope of the wage variables, the author finds that the inclusion of earnings from secondary jobs, overtime and bonuses and their corresponding hours of work in the definition of the wage variable increases significantly the estimated tenure effect. In addition he suggests that, at least for the workers paid by the hour, the '*hourly wage rate on main job*' is a better measure of hourly wage rate. It is less error-ridden than variables based on annual declarations and its scope is more adequate for the examination of the wage-tenure profiles. Overall, Lefranc concludes that the use of inadequate and error-ridden measures of earnings can lead to serious overestimation of the returns to tenure. While the accumulation of job-specific seniority plays a significant role in the evolution of individual wages, the returns to seniority are much lower and less persistent that those suggested by Topel.

2.2.6 European Studies on Seniority-Earnings Profiles

Although the literature on tenure-wages growth models is mainly dominated by US studies, there are various researchers who examine this issue using European surveys. Barth (1997) in a Norwegian study examines the relationship between seniority and wages. In particular, the author addresses the question of whether the seniority-wage profiles arise within or between firms. If workers are more likely to stay longer in high-paying jobs, then seniority effect should arise between firms. This is what AF (1987a) and AS (1987) in their studies referred to as job/match heterogeneity. In order to correct for heterogeneity among firms, the author proposes the use of a fixed-effect model based on within-firm variation only, where all variables are measured as deviations from their firm-specific mean. The fixed-effect model is preferable to the alternative random effect model, since there is potential correlation between the firm-specific effects and the other explanatory variables. The data set is from the Norwegian Survey of Organizations and Employees (NSOE) conducted in 1989. This is a sample of private-sector employees only, representative of wage earners in firms with more than one employee. The fact that each individual is observed only once means that the fixed-effect model cannot correct for possible fixed effects across individuals. However, it is able to single out the seniority effect on wages arising within firms from the total seniority wage effect. A wage equation model is estimated based on three different specifications: a standard regression on the pooled sample, a random effects model and a within-firms fixed effects estimator. The findings are quite robust with respect to the choice of model. Ten years of seniority within the firm increase wages by around 3.5 per cent. According to the author, since the seniority-wage profile derived from the within-firm variation only is as steep as the one estimated on the aggregate, seniority effect probably arises within firms.

Furthermore, Barth examines whether he can find support for the two most prominent explanations of the positive relationship between seniority and wages: the human capital theory (Becker, 1975) and the theory of deferred payment (Lazear, 1981). For the examination of the latter, he interacts the use of piece-rate payment with firm-specific seniority. The presence of a piece rate actually links wages with individual productivity. If Lazear's theory can explain the positive seniority effect, then piece-rate workers should have no return to seniority within the firm, since they would not be covered by seniority schemes. Indeed, Barth's estimates are in accord with the deferred payment theory. The seniority effect is negligible for piece-rate workers. The author assesses whether the human capital is behind the observed seniority-wage profiles with the use of a variable measuring the job's required level of on-the-job training (in duration) and a rough distinction between general and specific skills requirements, based on individual responses. The human capital theory implies that the more demanding, in respect to on-the-job training, a job is, the higher the pay and the larger the tenure effect are going to be. The findings provide support for the former, indeed higher training requirements give higher wages. However, the seniority effect declines with the on-the-job training requirements on the job, which contradicts with the human capital theory. The author also tries to distinguish between general and firm-specific skills. The interaction between specific training and seniority has a significant negative effect that is against the human capital interpretation. An explanation that Barth suggests for this negative interaction effect for firm-specific skills is that since the firm rewards the firm-specific training requirements there is no so much need for a steep seniority-wage profile.

Overall, Barth's study provides some rather interesting findings. Seniority effect appears to rise within firms, any effect driven by the fact that high-paying jobs tend to survive longer is either negligible or offset by mechanisms like better job matches for those who change jobs. Furthermore, the author provides support to Lazear's delayed compensation theory, since piece-rate workers experience insignificant seniority effect. However, the results contrast human capital theory. Workers in jobs with demanding training requirements experience lower returns to seniority compared to employees in jobs with small training requirements. In addition, higher levels of firm-specific training requirements are related to less steep seniority-wage profiles.

Dustmann and Meghir (1999) in a recent study develop and estimate a human capital model of wage growth based on learning by doing, using data from the German Social Security records for the years 1975-1990. Among their findings, they show that simple OLS regressions overestimate the returns to experience and tenure. Moreover, the estimated returns to tenure are quit small, ranging from 0.38 to 1.6 per cent annually, where the lower point estimate is obtained when allowing for heterogeneity in the returns to tenure across firms. In any case however, the wage premia accounted to job tenure are very small. Finally one of their interesting finding is that most of the wage growth appears to be transferable. The authors recognise though that their results may not be directly comparable to results of studies based on USA data (e.g. Topel 1991), due to the differences in timing of the acquisition of human capital, accounted for by the different way by which on-the-job training is organised in the two countries.

Sloane and Theodossiou (1993) provide the first study on the effect of tenure on earnings using British data. Based on the 1986 Social and Economic Life Initiative[3] (SCELI) survey, they estimate the returns to tenure separately for each sex. The methodology employed in order to obtain consistent estimates of the returns to tenure relies on the estimation of a simultaneous earnings-tenure system of equations, using a three-stage least squares (3SLS) estimation procedure. For the identification of the tenure equation, individual and job characteristics that are assumed to influence earnings but not tenure are used. Similarly, the wage equation is identified with variables proxies of the firm's demand for labour and individual or job characteristics that affect tenure but not earnings. The authors provide a very informative discussion on the choice of explanatory variables and on their expected behaviour in these two models.

The findings from the tenure equations are quite similar to what we would probably expect. Education is likely to make individuals more mobile (this is true for both sexes), hence reduce expected duration of tenure. Job instability of the individuals, proxied by unemployment experience and number of voluntary job quits, is negatively related to tenure. Last-in first-out redundancy policies, on the other hand, have a positive relationship with tenure, since such rules tend to increase the

[3] This survey includes only six labour markets (Aberdeen, Coventry, Kirkcaldy, Northampton, Rochdale, Swindon). Potentially, the fact that the survey is based on these six distinct geographical areas, rather than a nationally representative sample, may be a weakness.

average seniority of remaining employees. Similarly, the presence of union representation has a positive effect on the duration of tenure. Furthermore, pay incentive schemes appear to increase only the tenure of male employees; as for their female colleagues the estimated effect is negative and insignificant. Finally, in the case of male employees, seniority does not appear to be affected by earnings, while for the female employees there is a significant and positive relationship.

Turning to the earnings equations, as expected, education and establishment size have a positive effect on wages. Unemployment experience has a negative effect only in the case of male employees, but men also enjoy larger returns to labour market experience compared to women. In addition, marriage has a positive earnings effect in the male equation and a negative in the female model. More crucially though, tenure does not appear to have any effect on the earnings of male employees, whilst it has a strong positive effect in the case of female individuals. This finding can be interpreted in conjunction with the fact that the number of voluntary quits is strongly significant in the male earnings equation, but insignificant in the earnings equation for women. As the authors suggest "*men gain from mobility in that any positive return to tenure is obscured*" (pp. 429).

Overall, the analysis suggests quite distinct patterns between the sexes. For men earnings have no significant effect on the duration of tenure and tenure, on the other hand, does not influence positively earnings. While for women, higher earnings increase the probability of staying more with a given firm and longer tenure is rewarded by higher earnings. These contrasting results can be interpreted with the differential lifetime labour force behaviour between men and women. Men gain from mobility especially in the early stages of their working lives, while women with less employment opportunities available are more difficult to change employer, so according to the authors the underlying connection between tenure and earnings is revealed.

Theodossiou (1996) in a later study using the same data (SCELI 1986) examines the employer-tenure effect, distinguishing between employees with promotion prospects and those without. The idea behind this distinction lies in the two-tier labour market hypothesis. Within this framework, firms offer their most highly valued employees promotions opportunities and reward their tenure, loyalty in the firm, in order to discourage labour turnover and interfirm mobility. Employers are also quite likely to adopt a non-promotion strategy for part of their labour force. The workers related to the latter experience flat tenure-wage profiles and their wages are rather sensitive to changes in product demand.

Theodossiou's analysis is based on the estimation of two wage equation models, one for employees with promotion prospects and one without, where promotion status is modelled as an endogenous variable. Individuals, based on their characteristics, have different probabilities on getting promoted. These promotion opportunities however influence their wages. Therefore, the observed earnings distributions of the promotion and non-promotion employees would not be independent of promotion status. The author presents estimates based both on OLS and the AS instrumental variable model, although he argues that heterogeneity bias is not of major importance. The selection model should capture part of the unobserved individual and job match effects. Furthermore, the main interest is in the comparison of the slope coefficients between the two sectors. So unless the heterogeneity bias affects these comparisons, it does not raise any concern. The estimates from both OLS and IV yield similar results about the wage-tenure profiles. Employer-tenure appears to have a significant and positive role only for those employees with promotions prospects. The derived returns to tenure in this sector are higher by almost 19 per cent (for the IV model and 16 per cent for OLS) compared with those in the non-promotion sector, which are statistically insignificant. The plotted tenure earnings profiles for employees in the former sector display a rising and decelerating trajectory that appears to reach the maximum after approximately ten years of tenure. On the contrary, the wage-tenure profiles for those with no promotion prospects are almost flat.

Booth and Frank (1996) are the first to present a study on the importance of seniority in the wage determination process using data from the BHPS. In particular they use data from the first wave of BHPS (1991) and examine whether wages rise more with seniority in workplaces with or without union representation. Their findings suggest that tenure (measured at current job/position rather than at current employer) has a quite modest and statistically insignificant effect in both union and non-union sector. Finally, Manning (1998) using data from LFS (covering the period between March 1993 to February 1996) shows how a search model can predict the nature of the relationship between wages, labour market experience and tenure. Within this framework, his analysis suggests that the observed tenure effect can be interpreted by a '*job-shopping*' model, instead of the human capital theory. While the return to experience appear to be driven partly by the search activity and partly by the actual accumulation of general human capital, the search model can overpredict the return to tenure implying that the return to tenure is broadly consistent with the '*true*' tenure return being close to zero.

2.3 Data Description

2.3.1 BHPS Sample Characteristics

The empirical analysis throughout the thesis is based on the British Household Panel Survey (BHPS), covering the period between September 1991 and May 1999 (*Waves 1-8*). This is a nationally representative household panel survey of around 5,500 households (containing about 10,000 persons) randomly selected South of the Caledonian Canal (thus excluding the North of Scotland and Northern Ireland). The first survey of the BHPS was conducted in the autumn of 1991, and annually thereafter (the period each survey covers is reported in ***Table A.2.1***). Each BHPS survey is referred to as a wave, e.g. the first survey in 1991 is *Wave 1*, the second *Wave 2* and so onwards. The sample used in my analysis is restricted to individuals who are Original Sample Members (OSM). These are mainly individuals within the randomly selected initial sample drawn from the Postcode Address File. All OSMs are followed throughout all future waves of the BHPS where possible. In addition, other respondents not initially included in the initial sample may be added to the group of OSMs when associated with an OSM in the formation of a new household[4].

Continuing on the description of the sample used in the thesis, the individuals considered are male and female individuals between 18 and 60 years of age, who reported working full-time (at least 30 hours per week) and are not self-employed. Individuals with missing information or imputed data in the variables used in the empirical analysis are excluded from this sample. The earnings variable mainly considered in the estimated wage equations is the natural logarithm of the nominal gross average hourly wage, defined as the usual weekly pay divided by the usual

[4] The criterion is that the individual needs to be a parent of an OSM's baby, in a newly formed household.

paid hours in a week, including overtime paid. For the construction of the hourly wage, usual paid hours and overtime paid hours in a week are normalised to equal a maximum of 60 hours for the former and 12 hours for the latter. Therefore, an upper bound is imposed on the reported hours of work in order to avoid potential biases from measurement errors in the estimates of interest. The reason I use hourly wage rates instead of weakly or monthly rates is mainly because there may be different patterns that govern the employment conditions and labour supply preferences of male and female employees. Since not all individuals work the same number of hours, their weekly or monthly wages are bound to differ. Using hourly wage rates though, allow us some degree of uniformity across the whole sample, as we incorporate any dispersion in the hours of work.

The BHPS provides valuable information on the employment history of the respondents, which is very useful for the construction of some human capital variables. At each wave their current labour market status is reported, as well as their employment history for the period beginning on 1st of September a year prior to the interview. In addition, information on the complete labour market history of the individuals, since leaving full-time education for the first time, is recorded in the second wave and, complete job data are also collected at the third wave (1993). Based on these records, I am able to follow my sample of individuals since the beginning of their labour market history and construct their total actual labour market experience (full-time and part-time) and current employer-tenure. In the *Appendix* of this chapter, I provide a detailed description on the method employed for the construction of those variables.

For the purposes of my analysis in this chapter, I use three different samples. The first is a pooled sample, where all individual regression samples across the eight waves are included. The other two are panel samples: an unbalanced and a balanced. The unbalanced panel sample is a sample of employees who appear at least twice, thus the maximum panel length of any sample member is eight years, while the minimum panel length is two years. In the balanced sample, only employees who are observed in all eight waves are included. Therefore, the balanced panel sample contains eight observations for each individual. In *Table A.2.2* (Appendix) I provide some summary statistics[5] of these three samples drawn from the eight waves of BHPS, on the main human capital variables and the hourly wage rate that I use in *Chapter 2. Tables A.2.3* and *A.2.4* that follow next provide the averages and standard deviations of these variables of interest drawn from the pooled sample, separately for the male and female employees, summarised per wave.

A brief examination of these raw data is quite indicative of some patterns that govern the labour market behaviour and history of the male and female individuals. From the means on the pooled sample in *Table A.2.2* we can see that on average male employees have spent roughly a year more with their employer than their female peers. Furthermore, male individuals appear to experience mainly full-time employment spells (with an average part-time working experience around half a year), while female individuals spend around three years on part-time jobs on average. In accordance to these patterns and as we would probably expect, male individuals seem to have longer employment history with less spells of unemployment or out of the labour market, compared to the female sample. A comparison between actual labour market experience and potential labour market experience[6], a popular proxy of working experience in the literature, indicates that

[5] I should underline here that these descriptive statistics refer to the male and female sample of full-time employees only, and not to the whole BHPS sample.

[6] Measured as the difference between current age and age when left full-time education for the first time.

while there is no significant variation between the two measurements for the male individuals, for the females there is a substantial difference. Since the average age composition of the two samples (male and female) is fairly similar, this observed difference should probably be attributed to either gender discrimination issues or to the particular nature of women's labour market behaviour, who for maternity and other family reasons spend more time out of the labour market. Finally, male employees also earn on average higher hourly wages than their female colleagues. Again some candidate reasons for these discrepancies may be sex segregation in particular jobs and occupations and exclusion from prestigious, high-paying jobs, along with those already mentioned above. These observed differences in the raw data between male and female employees are also depicted in the averages on the two panel samples (unbalanced and balanced), which compose a fairly similar landscape. Overall, there appears to be a different attitude between male and female individuals towards labour market attachment. In the next section, I further elaborate this issue and address the implications that may be raised within the framework of my empirical analysis.

2.3.2 The Traditional Empirical Division Between Male and Female Employees

Throughout my thesis I present earnings equation models and estimates on the returns to accumulated skills in work. The question raised here is how relevant and appropriate is to divide the sample into male and female employees and estimate separate wage equations, given the transformation that male and female labour supply has undergone and the legislative changes on discrimination issues[7] over the last decades. The discussion above on the raw data reveals some distinct gender patterns on labour market attachment. Male individuals on average appear to

[7] Equal Pay Act (1970) and Sex Discrimination Act (1975, 1992).

experience lengthier tenure in their jobs compared to their female peers. Furthermore, a comparison between potential work experience and actual experience shows that males are more attached to the labour market, while female individuals spend a significant amount of time unemployed or, out of the labour market. Although this analysis relies on basic descriptive statistics, I believe it is indicative of the true trends that govern labour market supply and behaviour.

Booth *et al.* (1999), using the first five waves of BHPS, present a study where they formally compare men's and women's participation rates in Britain. Despite the fact that there is convergence in men's and women's labour market participation rates, the study suggests that the rates still differ and so does the degree of longitudinal persistence. In particular, Booth at al. find that the year-on-year persistence in paid work propensities is higher for males than for females indicating females have less labour force attachment than males in the UK. They also find that the year-to-year persistence of non-work is higher for female than for males. Furthermore, while non-job elapsed spell lengths for women are more than double the length of those for men on average, men experience longer job spell duration compared to women, although the differentials between sexes are smaller in that case. The authors suggest that the principal sources of differences between the sexes in their probabilities of paid work are differences in observable characteristics and differences in rates of return to those characteristics. Specifically, women in the sample, compared to men, are not as highly educationally qualified, have less prior full-time working experience and appear to have greater responsibilities for children, on average. Nonetheless, the key determinants of these observed differences in the paid-work propensities seem to be the differences in the coefficients on household structure, in particular the number and age of children. Although, the impact of having children significantly reduces the probability of being in work for both men and women, the magnitude of the effect is dramatically higher for women. A finding that conforms with the traditional view that women have to bear the burden of child-care. "*In spite of the rhetoric about shared family and work responsibilities and the 'new men' of the 1990s, family responsibilities have a much greater disincentive effect on the probability of being in paid work for women than they do on the probability for men*" (pp. 189).

Booth *et al.*'s study provides sufficient evidence to support the decision to examine the tenure-earnings profiles separately for the male and female sample. Men and women show distinctively different patterns in their labour market behaviour and attachment. Therefore, estimates on a pooled sample composed of both sexes will probably conceal this diversity in their labour supply. One issue that arises though from the estimation of an earnings equation on female employees only is the potential sample selection bias in the estimates of interest. Since women still appear to be less attached to the labour market compared to men, their participation decision may be a source of selectivity bias. In a wage equation framework, the researcher focuses only on individuals who are working, however the question of interest here is whether working women are representative of the population of women as a whole, or not. If the absence of non-participants involves the omission of observations, which are not missing at random, OLS estimates on an earnings regression can potentially be biased and inconsistent. The classical regression model does not allow for the sample selection problem, which may occur when for instance women leave the labour force for domestic reasons. If those who quit work are not a random selection from the female sample, then OLS will be inconsistent. Although this is an interesting topic, the examination of selectivity bias in the female wage equation model exceeds the purpose of my study. Furthermore, taking account of this selectivity requires data on a suitable instrument that affects labour market participation but not wages. However, finding or, constructing such an instrument can often be a rather difficult task. Therefore throughout the empirical analysis in my thesis I do not address this issue and I interpret the estimated coefficients as the true returns to the variables of interest.

2.4 Estimating the Returns to Employer-Tenure

2.4.1 OLS Estimates

Despite the fact that OLS method has been criticised of overestimating the contribution of tenure in a wage equation due to possible endogeneity bias (AF, 1987a; AS, 1987 among others), we can still think of the OLS estimates as a '*benchmark*', a reference point for our estimations when using alternative techniques. Therefore, in this section I examine the OLS returns to employer-tenure based on a standard Mincer (1974) wage equation. In particular, the analysis is focused on the effect employer-tenure has on hourly pay and how this effect may vary according to the functional form of the model used, the different methods of time trend and business cycle wage adjustment, as well as the inclusion of actual instead of potential labour market experience.

The estimated model is a log linear wage equation, outlined as:

$$W_{ijt} = \alpha + \beta_1 E_{ijt} + \beta_2 T_{ijt} + \beta_n X_{ijt} \tag{2.11}$$

where i is the individual in job j at period t and E_{ijt} refers to labour market experience, T_{ijt} is the employer-tenure and X_{ijt} is a vector of n other regressors. The dependent variable used in the estimated wage equations in this section, unless otherwise is stated, is the log of the nominal gross average hourly wage. The other regressors included in the *Basic Model* (*Model 1*) are: age left education[8], a

[8] Defined as age left school or, in the case of further education, age left further education if it is less than or equal to 25.

quadratic in employer-tenure (measured in years divided by ten, i.e. decades), a quadratic in potential labour market experience (measured in years), dummies for individual's skills and a time trend, that takes values from 1 to 8 according to the wave the observation belongs to. The model is estimated for the pooled sample and separately for the male and female employees and presented in ***Table 2.1***, first column. The derived effect of 5, 10, 15 and 20 years of employer-tenure are also provided on the table (*T5*, *T10*, *T15*, *T20* respectively). What stands out from these estimates is the fact that in all cases the returns of employer-tenure are quite modest (the effect ten years is 4.7 per cent for the pooled sample and 5.7 per cent and 1.6 per cent for the male and female) and that there is a noticeable difference between male and female employees.

The *Basic Model* is re-estimated using alternative control vectors, columns 2 to 5 in ***Table 2.1***. The model presented in the second column is the *Basic Model* with the addition of regional dummies and some controls the workplace characteristics, one-digit industry dummies and establishment size dummies (*Model 2*). The third model estimated includes regional dummies and some occupational and qualification dummies (*Model 3*). The model presented in column four uses as regressors, apart from those included in the basic model, regional dummies, workplace-characteristics controls (establishment size and one-digit industry), as well as controls for occupation and individuals' qualifications (*Model 4*). The last specification examined (*Model 5*) includes all the regressors used in *Model 4* plus two dummies for union coverage in the workplace and union membership[9].

[9] These five wage equations are estimated many times throughout this chapter. Therefore, in order to avoid repetition, for the rest of the analysis I refer to them as *Models 1-5*, without mentioning the regressors each model includes.

Looking at the presented estimates of the employer-tenure effect from these four alternative specifications, we can see that the picture has slightly changed, with the returns of ten years of tenure varying from 6.7 to 7.3 per cent for the pooled sample, 4.6 to 6.9 per cent for the male employees and 4.3 to 7.6 per cent for the female employees. Nevertheless, the estimated effect is still appears to be modest, not exceeding the 8 per cent in any case.

2.4.1.1 Examination of Alternative Functional Forms

The analysis in this section is focused on the choice of the functional form and on the sensitivity of the returns to employer-tenure to different functional forms. For the purpose of the analysis five alternatives to the basic quadratic wage equation model (*Model 1*) are examined. The models are estimated separately for the pooled and the male and female full-time employees and presented in *Tables 2.2-2.4*.These models include the *Basic Model* with the addition of a dummy variable for employer-tenure greater or equal to one year (*row 2*), a dummy for tenure greater or equal to 6 months (*row 3*), an interaction term between the age individuals left education and their potential labour market experience (*row 4*) and higher order polynomials in employer-tenure (*rows 5* and *6*).

The inclusion of a dummy for tenure length greater than 6 months or one year has, not surprisingly, decreased the estimated effect of ten years of employer-tenure in all cases. It would be a reasonable argument to assume that job-specific skills are mostly acquired during the first short period in a new job and that the accumulation of skills continues after that period but at a smaller rate. The findings in *rows 2* and *3* simply confirm that hypothesis, where the addition of a dummy for tenure length has reduced the contribution of ten years of employer-tenure. In the estimated models presented here the potential labour market experience is included in the vector of regressors, which is estimated by taking the difference between the current age of the individual and his/her age when left education. Therefore, individuals of the same age are expected to have less years of potential labour market experience when they are well educated rather than when they have the '*basic*' education. The interaction term between age left education and years of potential labour market experience controls this '*relationship*' between these two variables. The estimates presented in *row 4* (***Tables 2.2-2.4***) suggest that the effect of employer-tenure remains the same, for the pooled sample and the male employees, when this interaction term is included in the regressors. Only in the case of female employees is the magnitude of tenure effect slightly increased to 2.5 per cent, but the effect still is statistically insignificant even in that case.

The estimates presented in ***Tables 2.2-2.4*** may shed some light to the question of how employer-tenure should be entered into the wage equation, quadratic, cubic or any other higher order polynomial. The inclusion of cubic in tenure appears to increase significantly the effect on the log wage for all the samples, pooled, male and female. The coefficients of tenure are individually significant even at a 5 per cent level of significance. Further, the join significance of the tenure terms in the wage model[10] and the significance of the effect of ten years of tenure[11] are tested (tests are not presented here). In both cases, the H_0 is strongly rejected, suggesting that the 3rd order polynomial in tenure may be the appropriate form. Hence, from the rest of my analysis I adopt the cubic in tenure specification, and so the *Basic Model* now includes age left education, a cubic in tenure, a quadratic in experience, dummies for skills and a time trend.

---

[10] H_0: $\beta_1 = \beta_2 = \beta_3 = 0$

[11] H_0: $\beta_1 + \beta_2 + \beta_3 = 0$, i.e. the returns of ten years of tenure are equal to zero.

The five models presented in ***Table 2.1*** are now re-estimated, for the pooled sample and male and female employees, using cubic instead of quadratic in tenure. The estimates are shown in ***Table 2.5***, where the effect of 5, 10, 15 and 20 year of employer-tenure on the log wage is presented as well. Compared with the estimates in ***Table 2.1***, it appears that the inclusion of 3rd order polynomial in tenure has increased the returns to ten years of employer-tenure by at least 50 per cent in most cases. In particular, the estimated effect of ten years of tenure on the log wage now ranges from 7.9 to 11.4 per cent for the pooled sample and from 7.6 to 11 per cent and 6.4 to 12.8 per cent for the male and female employees respectively. The inclusion of 3rd order polynomial in tenure has significantly altered the estimated tenure effect suggesting that the contribution of the employer-tenure is better described in a wage equation like the one below:

$$W_{ijt} = \alpha + \beta_1 E_{ijt} + \beta_2 E_{ijt}^2 + \beta_3 T_{ijt} + \beta_4 T_{ijt}^2 + \beta_5 T_{ijt}^3 + \beta_n X_{ijt} \quad (2.12)$$

Even though the 3rd order polynomial in tenure appears to explain better the contribution of employer-tenure, the estimated effect remains modest and in no case does the ten-year tenure effect exceed the 11 per cent and 13 per cent, for the male and female employees, respectively.

2.4.1.2 Real Hourly Wages and Actual Labour Market Experience

So far the analysis is focused on nominal hourly wages. However it would be interesting to examine whether time trend can be a source of variation in the estimated returns to employer-tenure, so here I examine several treatments of time trend. ***Table 2.6*** summarises the returns of 5, 10, 15 and 20 years of tenure estimated on 6 different models. The first model is the *Basic Model* that includes nominal hourly pay and a time trend (*row 1*) and the second model includes 7 wave dummies instead of the time trend (*row 2*). The following two models include the real hourly wage, based on the *Retail Price Index* (RPI), instead of the nominal (*row 3*), with the addition of a time trend in the second model (*row 4*). Finally, the remaining two models use the real hourly pay, based on the *Average Earnings Index* (AEI) (*row 5*), with the inclusion of a time trend in one of them (*row 6*). The information on RPI and AEI is taken from the National Statistics. RPI[12] refers to annual average with base year 1987 and AEI[13] is the annual average based on all the employees working in the main industry sectors with base year 1995. The average nominal and real hourly wage rates for men and women are presented per calendar year in ***Table A.2.3.***

The OLS estimates presented in ***Table 2.6*** simply suggest that there is very little variation in the returns to tenure based on which time trend is used. The estimated impact of ten years of employer-tenure on the log wage is estimated to be around 9.4 per cent for the male employees and roughly 6.4 per cent for the female employees. One thing though that is worth mentioning is the differing effect that deflating the nominal wage with the RPI (*row 3*) and de-trending the nominal wage with the AEI (*row 5*) have on the estimated returns to tenure. As it is shown in ***Table 2.6***, the returns to tenure are greater when using the RPI to deflate the nominal wage (*row 3*) than when de-trending the nominal wage with AEI (*row 5*). However, when I include a time trend in both cases (*rows 4* and *6*) it brings the estimated returns to tenure back into line with the rest of the estimates (*rows 1* and *2*). The

---

12 "*The Retail Price Index (RPI) measures the percentage changes month by month in the average level of prices of the goods and services purchased by the great majority of households in the United Kingdom.*" Source: Office of National Statistics

13 "*The Average Earnings Index (AEI) is designed to measure changes in the level of earnings i.e. wage inflation in Great Britain.*" Source: Office of National Statistics

inclusion of the time trend appears to control for the difference between the trend in the AEI and the RPI and the actual trend in the BHPS sample used in my analysis.

The BHPS data set provides all the necessary employment history information that enables the construct of the actual labour market experience. Therefore, now I examine what impact the inclusion of actual experience, instead of potential, in the wage equation has on the estimated returns to tenure. ***Table 2.7*** presents estimations of the *Basic Model* on the male and female pooled, unbalanced and balanced sample using alternativly potential and actual experience. In all cases, it appears that the inclusion of actual experience, instead of potential experience, reduces the estimated returns to employer-tenure. The magnitude of this effect varies noticeably between male and female employees. For the male sample the estimated returns to ten years of tenure decrease from 9.4, 9.4, and 5.9 to 7.7, 7.7 and 5.2 per cent for the pooled, unbalanced and balanced sample, respectively. While for the female employees the effect is more dramatic with the returns to ten years of tenure falling from 6.4 or 5.4 to 1.3 and 0.4 for the pooled and unbalanced sample, giving even a negative effect when estimated on balanced sample.

The analysis so far, based on OLS, has shown that the contribution of employer-tenure in the wage determination is quite modest, with the estimated impact of ten years of tenure not exceeding 10 per cent in most of the cases, both for male and female full-time employees. In the next part of this chapter, I address the issue of potential endogeneity bias in the least square estimates and explore the robustness of my findings using alternative estimators suggested in the literature.

2.4.2 Altonji & Shakotko's (1987) Instrumental Variable Technique

AS (1987), when examining the impact of tenure on wages, proposed the use of an instrumental variable to deal with the endogeneity problem deriving from the fact that tenure is likely to be related to unobserved individual and job match characteristics that affect wages. The authors suggest the use of the difference between the employer-tenure and the average employer-tenure for the individual as a valid instrument of employer-tenure. More specifically, assume a wage equation model:

$$W_{ijt} = \beta_0 X_{ijt} + \beta_1 T_{ijt} + \beta_2 T_{ijt}^2 + \varepsilon_{ijt} \tag{2.13}$$

$$\varepsilon_{ijt} = \mu_i + \varphi_{ij} + n_{ijt} \tag{2.14}$$

for the individual i, in job j at period t, where X_{ijt} is a control vector that includes labour market experience. According to their analysis a valid instrument for the tenure is $\Delta T_{ijt} = T_{ijt} - \overline{T}_{ij}$ where $\overline{T}_{ij}$ is the average employer-tenure for the individual. The authors argued that ΔT_{ijt} sums up to zero over the sample years in which the individual i is in job j. Furthermore, the instrumental variable, T_{IV}, is orthogonal to the error components μ_i and φ_{ij}, which are constant during job j. If T_{IV} is also orthogonal to the transitory error component η_{ijt}, then T_{IV} is a valid instrumental variable.

In the analysis presented here, two different methods are used to construct the instrumental variable. The time difference between two consecutive waves of the BHPS can be defined as either one year (*method 1*) or as the actual duration between consecutive interviews for each individual (*method 2*). In both cases the tenure value used to construct the mean tenure $\overline{T}_{ij}$ is the one from the wave that identifies the maximum length of time with employer. For example, using the first method, for an individual who is observed in all the waves (wave 1 to 8) if his employer-tenure in wave 8 is greater than 7 years (difference between the latest and the earliest wave observed) then this individual hasn't changed employer over the sample years. So, the average employer-tenure for this individual will be the tenure at wave 8 minus 3.5 (the half of the difference between the latest and the earliest wave he was observed). Similarly for the second method, with the only difference that instead of using the difference between the latest and the earliest wave the individual was observed, I use the length of time between the interviews of the latest and the earliest wave the individual was observed, given that the employer-tenure in the latest wave exceeds this period.

Adopting AS's methodology here, I instrument the tenure polynomial terms with the deviation from their means, defined as:

$$T_{IV} = T_{ijt} - \overline{T_{ij}} \quad (2.15)$$

$$T_{IV}^2 = T_{ijt}^2 - \overline{T}_{ij}^2 \quad (2.16)$$

$$T_{IV}^3 = T_{ijt}^3 - \overline{T}_{ij}^3 \quad (2.17)$$

In the following sections estimates on the return to employer-tenure, using the AS instrumental variable method, are presented and the sensitivity of the estimated tenure effect is examined to different treatments of time trend, the inclusion of actual experience and the use of alternative control vectors.

2.4.2.1 Estimation of the Basic Model

In this section I provide some initial estimates on the returns to tenure using the AS instrumental variable method. *Table 2.8* presents estimates of the basic model separately for the male and female unbalanced sample of full-time employees, where the instrumental variable is constructed using both methods. The model used here includes a cubic in employer-tenure and a quadratic in potential labour market experience. In addition to the estimation of the model, a Hausman test is performed. The general idea of a Hausman test is that two estimators are compared. One which is consistent under both the null hypothesis and the alternative (the instrumental variable estimator here) and one which is consistent and typically efficient only under the null hypothesis (OLS estimator). The Hausman test examines whether there is sufficient difference between the coefficients of the instrumental variables regression and the standard OLS and it is best interpreted as evaluating whether OLS is a consistent estimator of the model. Therefore, rejection of the null hypothesis indicates that OLS is an inconsistent estimator for this model. All the estimates and the Hausman test are shown in ***Table 2.8***.

The estimated returns to 5, 10, 15 and 20 years of tenure for both male and female employees are relatively consistent across the two methods employed. In the case of male employees, the estimated effect of ten years of tenure is 4.5 per cent, but statistically insignificant. In addition, the Hausman test indicates that OLS is a consistent estimator of the model, implying that endogeneity bias is probably not a serious problem in the sample. Similarly for the female employees, tenure does not appear to have any effect on wages. The Hausman test in this case though suggests that OLS is an inconsistent estimator of the model. The wage equation is re-estimated in ***Table 2.9*** with the basic model including a quadratic in tenure this time, as AS used in their analysis. The estimates do not differ a lot from those shown in ***Table 2.8***. The effect of ten years of tenure for the male employees is around 5 per cent, while for the female employees tenure effect still appears to be negligible.

2.4.2.2 Treatment of Time Trend

AW (1997) underline the importance of wage treatment over time. Here I examine six different ways of time treatment using the *Basic Model*, as I did with the OLS estimates (*Table 2.6*). The models are estimated separately for the male (*Tables 2.10* and *2.12*) and female full-time employees (*Tables 2.11* and *2.13*) both from the unbalanced and balanced sample. The estimates presented in *Tables 2.10* and *2.11* are based on models with a cubic in employer-tenure and a quadratic in potential labour market experience, while those in *Tables 2.12* and *2.13* include a quadratic both in tenure and potential experience, as AS do in their analysis. From the previous estimates we show that the choice of the method to construct the instrumental variable has no impact on the findings, therefore for the rest of my analysis I use the instrumental variable derived from the second method.

The estimates presented in *Table 2.10* imply that the returns to tenure are relatively sensitive to the choice of wage treatment over time. However for the unbalanced sample the effect of tenure is quite similar when using nominal wages and a time trend or wave dummies and when using the de-trended nominal wage (AEI) and a time trend, with the estimated returns to ten years of tenure slightly lower than 4.5 per cent. Yet, tenure has a significant positive effect only in the model based on the deflated nominal wage (RPI), where the estimated returns to ten years of tenure are 6.8 per cent. On the other hand, the estimates on the male balanced sample imply that tenure has no significant effect on wages, irrespective to which model is chosen. Furthermore, for both samples, Hausman test is almost uniformly in favour of the OLS estimator. In *Table 2.11* the estimates on the female full-time employees are presented. What stands out of those estimations is that tenure appears to have a significant effect only in the model that uses the deflated nominal wage (RPI) for both the unbalanced and balanced sample. The estimated returns to ten years of employer-tenure are around 12 per cent in the case of the unbalanced sample and a bit lower for the balanced sample, roughly 10.2 per cent. According to Hausman test and contrary to the estimates on the male sample, OLS appears to be an inconsistent estimator for the female employees in most of the cases.

The picture does not change radically when the models are re-estimated using a quadratic in tenure. In particular from *Table 2.12*, it appears that tenure has a significant effect only in the case of the model that uses the deflated nominal wage (RPI), estimated on the male full-time employees unbalanced sample. Compared with the estimates presented in *Table 2.10*, the effect now of ten years of tenure is slightly higher, around 7.7 per cent. Similarly for the female employees, *Table 2.13* suggests that tenure has a positive and significant effect when estimated on the real hourly wage, based on the RPI, for both the unbalanced and balanced sample. The magnitude of this effect is larger compared to the estimates presented in *Table 2.11*. Here, the effect of ten years of tenure is 12.7 per cent for the unbalanced and 11 per cent for the balanced sample.

2.4.2.3 Actual Labour Market Experience and Alternative Control Vectors

This section examines the sensitivity of the returns to tenure to the inclusion of actual labour market experience, instead of potential, and of alternative control vectors to the estimated model. *Table 2.14* presents estimates on the male and female balanced and unbalanced sample. The model used for the analysis is the *Basic Model* that includes a cubic in tenure and a quadratic in experience. Employer-tenure appears to have a positive effect only in the estimates on the male unbalanced sample, where ten years of tenure have a contribution of 4.5 per cent when the model is estimated using the potential experience and slightly lower when actual experience is included, around 3.3 per cent. Nevertheless, all estimates on the male samples (unbalanced and balanced) are not statistically significant. Interestingly enough for the female employees, tenure is calculated to have a strong negative effect, mainly significant though when actual labour market is included in the model. Once again, Hausman test implies that OLS is a consistent estimator for the case of male employees, where the opposite is true for both the female samples. The models are re-estimated including quadratic in both tenure and experience and presented in ***Table 2.15***. The findings are fairly similar, suggesting no true tenure effect for the male employees and a significant negative effect for their female colleagues.

Finally, four groups of alternative control vectors are also considered, *Models 2* to *5* as described already in the analysis above (***Tables 2.16*** and ***2.17***). In the case of male employees, tenure is calculated to have a significant positive impact on wages only in the case of the unbalanced sample. Yet the estimated ten-year effect is below 10 per cent. On the contrary, the contribution of tenure on the wage determination of the female employees appears to be trivial. Overall, two things stand out from the analysis based on the AS-IV. First, employer-tenure does not have any sizable impact on earnings. In addition, it appears that OLS is a consistent estimator for the case of male employees, while the contrary is probably true for the female employees.

2.4.3 Topel's Two-Step Estimator

Topel (1991), for the estimation of the returns to employer-tenure, suggests a two-step estimator that controls for potential endogeneity bias. The methodology used in his analysis can be summarised in the following model. First let's assume a wage equation given by:

$$W_{ijt} = \alpha + \beta_1 T_{ijt} + \beta_2 E_{ijt} + \beta_3 T_{ijt}^2 + \beta_4 E_{ijt}^2 + \beta_5 T_{ijt}^3 + \beta_6 E_{ijt}^3 + \beta_7 T_{ijt}^4 + \beta_8 E_{ijt}^4 \quad (2.18)$$

Taking the first difference we have:

$$\Delta W = \beta_1 \Delta T + \beta_2 \Delta E + \beta_3 \Delta T^2 + \beta_4 \Delta E^2 + \beta_5 \Delta T^3 + \beta_6 \Delta E^3 + \beta_7 \Delta T^4 + \beta_8 \Delta E^4 \quad (2.19)$$

Since $\Delta T = \Delta E = 1$ (the difference between two consecutive periods is one year), equation (2.19) can be re-written as:

$$\Delta W = \beta + \beta_3 \Delta T^2 + \beta_4 \Delta E^2 + \beta_5 \Delta T^3 + \beta_6 \Delta E^3 + \beta_7 \Delta T^4 + \beta_8 \Delta E^4 \quad (2.20)$$

where $\beta = \beta_1 + \beta_2$, in other words β represents the *within-job wage growth.* Returning back to the wage equation model, we can re-write the model as:

$$\begin{aligned} W_{ijt} &= \alpha + \beta_1 T_{ijt} + \beta_2 T_{ijt} + \beta_2 \left(E_{ijt} - T_{ijt}\right) + \beta_3 T_{ijt}^2 + \beta_4 E_{ijt}^2 \\ &+ \beta_5 T_{ijt}^3 + \beta_6 E_{ijt}^3 + \beta_7 T_{ijt}^4 + \beta_8 E_{ijt}^4 + \text{control vector} \end{aligned} \quad (2.21)$$

or,

$$\begin{aligned} W_{ijt} &= \alpha + \beta T_{ijt} + \beta_2 \left(E_{ijt} - T_{ijt}\right) + \beta_3 T_{ijt}^2 + \beta_4 E_{ijt}^2 \\ &+ \beta_5 T_{ijt}^3 + \beta_6 E_{ijt}^3 + \beta_7 T_{ijt}^4 + \beta_8 E_{ijt}^4 + \text{control vector} \end{aligned} \quad (2.22)$$

then,

$$\begin{aligned} & W_{ijt} - \beta T_{ijt} - \beta_3 T_{ijt}^2 - \beta_4 E_{ijt}^2 - \beta_5 T_{ijt}^3 - \beta_6 E_{ijt}^3 - \beta_7 T_{ijt}^4 - \beta_8 E_{ijt}^4 \\ &= \alpha + \beta_2 \left(E_{ijt} - T_{ijt}\right) + \text{control vector} \end{aligned} \quad (2.23)$$

Topel's two-step method relies on the estimation of equation (2.20) initially, in order to get an estimate of the within-job growth (β), and in the second step the estimation of equation (2.23) that will provide us with an estimate of the experience effect (β_2). Then, the tenure effect (β_1) is simply the difference between the within-job growth and the tenure effect $(\beta - \beta_2)$.

For the replication of Topel's method I have to estimate the first difference in tenure and experience. In my analysis I follow two alternative ways of doing that. First I assume that the period between two consecutive waves of the BHPS is one year (*method 1*), or alternativly I use the length between the interviews of two consecutive waves as a measure of the period between the two waves (*method 2*). In both methods applied the tenure used for the construction of the first difference is the one from the wave that identifies the longest period of time with employer. Similarly the experience used is from the wave that identifies the maximum length of time in the labour market. Therefore, using the first method described, the first difference in tenure is given by:

$$\Delta T = T_t - T_{t-1} \text{ or } \Delta T = T_t - (T_t - 1) \tag{2.24}$$

and the first difference in the square of tenure is given by:

$$\Delta T^2 = T_t^2 - T_{t-1}^2 \text{ or } \Delta T^2 = T_t^2 - (T_t - 1)^2 \tag{2.25}$$

similarly also for the higher order tenure terms.

2.4.3.1 Basic Model Estimates Using the Two-Step Method

In this section some first estimates based on Topel's two-step method are presented. The model used in the first step includes 4th order polynomials in both tenure and potential experience, like in Topel's analysis. In the second step the estimated model is similar to the one described by equation (2.23), with a variable that measures the age individuals left education included in the regressors. The models are estimated separately for male and female full-time employees from the unbalanced sample. The wage used is the real hourly wage, based on the AEI. ***Table 2.18a*** presents the estimates from the first step. The first row in this table is the estimated within-job growth (β), while in the rest of the rows the coefficients of the higher order terms in tenure and potential experience are summarised. ***Table 2.19a*** shows the estimates from the second step. In particular the first column presents the estimated experience effect (β_2), while in the second column is the within-job growth (β), taken from the previous table. The third column of the table has the tenure effect (β_1), derived from subtracting the first column from the second one. Finally the returns to 5, 10, 15 and 20 years of employer-tenure are presented in the last four columns.

What stands out from the estimates presented in ***Table 2.19a*** is first of all the difference in the returns to tenure between the male and female employees. While for the male sample tenure appears to have a strong positive effect on the log wage, for the female employees the effect seems to be very small and negative. Furthermore, there is a noticeable difference in the estimated returns to tenure between the two alternative methods used, especially for the male employees. The returns to ten years of employer-tenure for the male sample are roughly 15.5 per cent when estimated with the first method and slightly below 10 per cent when the second method is used.

The process is repeated again but this time instead of using the real hourly wage based on the AEI, I use the deflated hourly wage (RPI). Like before the estimates from the first and second step are presented in ***Tables 18b*** and ***19b***. Comparing these findings with the ones based on the de-trended nominal wage, we can see that the picture has changed dramatically, especially for the female employees. The returns to ten years of tenure, estimated on the female sample, are now slightly below 9 per cent, irrespectively to which method is used. For the male employees the tenure effect has increased as well, ten years of tenure have an effect of 24 per cent and 18 per cent on the log wage, when *method 1* and *2* are used respectively. Still the estimated tenure effect appears to be larger when *method 1* is employed.

2.4.3.2 Wage Treatment Over Time

From the previous section it becomes apparent that the estimated returns to tenure are very sensitive to the wage treatment over time. The use of alternative real wage definitions, de-trended and deflated nominal wages, changes noticeably the estimates. Therefore, in this section I further investigate the time treatment effects as I did before in the case of least squares and instrumental variable estimators.

Tables 2.20 and *2.21* present the derived tenure effect for the male and female unbalanced and balanced sample. All estimates presented are based on the second method of constructing the first difference. The returns to tenure appear to be very sensitive to the different methods of wage treatment over time. Yet the inclusion or not of a time trend when real wages are used does not seem to alter the results a lot. For the unbalanced male sample, the returns of ten years to tenure, when estimated on the nominal wages, are roughly 47 per cent, no matter if a time trend or wave dummies are included. This effect is reduced significantly when the model is estimated on the real wage, based on the RPI, to around 18 per cent. These estimates are further reduced more when the de-trended nominal wage (AEI) is used, with the effect of ten years of tenure at 12 per cent. The picture is quite similar when the models are estimated on the balanced sample, with the returns to tenure modestly larger in all cases.

Similarly for the female employees, the estimated returns to tenure change dramatically across the various ways of wage treatment over time. Like in *Table 2.20*, the use of nominal wages gives the highest estimated tenure effect (ten-year tenure effect is calculated around 38 per cent and 35 per cent for the unbalanced and balanced sample), while the estimates on the real wage (AEI) suggest a small but negative tenure effect. The alternative estimates on the unbalanced and balanced sample do no change noticeably the returns to tenure, apart from the case when real wages based on RPI are used, where the tenure effect almost doubles for the balanced sample. A comparison between the estimates presented in *Tables 2.20* and *2.21* strongly suggests that, in all the cases examined, the returns to tenure are higher for the male employees. The analysis in this section showed that there is a significant diversity in the estimated tenure effect, depending on the way wages are treated over time. Therefore for the rest of my analysis, I will present estimates using both the deflated (RPI) and the de-trended (AEI) nominal wage.

2.4.3.3 Actual Instead of Potential Labour Market Experience

The question examined in this section is whether the inclusion of actual experience instead of potential alters the results at all. The model considered in the first step includes 4th order polynomials in both tenure and experience, while age individuals left education is added to the regressors of the model in the second step. The method of constructing the first differences in the tenure and experience terms is the one based on the period between two consecutive interviews (*method 2*).

Table 2.22a summarises the estimated effect of 5, 10, 15 and 20 years of employer-tenure, when the de-trended nominal wage is used. For the male sample the choice between actual or potential experience does not alter the results significantly. However the reported returns to tenure increase dramatically when the effect is measured on the balanced sample. While the returns to ten years of tenure are around 10 per cent for the unbalanced sample, the effect is doubled to 21 per cent when the balanced sample is used. In contrast, for the female employees the effect of tenure appears to be negative in all the cases considered.

The analysis is repeated again, but this time the returns to tenure are estimated on the deflated wage (RPI), *Table 2.22b* summarises the findings. The picture does not change dramatically for the male employees. The alternative use of potential and actual labour market experience does not affect the returns to tenure, with the effect of ten years of tenure around 18 per cent for the unbalanced sample and, like before, noticeably increased for the balanced sample, roughly above 26 per cent. The results are more interesting for the female employees, where the inclusion of actual experience appears to decrease the returns to tenure for both the unbalanced and balanced sample. In particular, for the unbalanced sample the effect of ten years of tenure falls from 8.5 per cent to 6.5 per cent and for the balanced sample from 5.8 per cent to only 2.1 per cent. Furthermore, the tenure effect is smaller when estimated on the balanced sample, than on the unbalanced, giving an opposite picture to the one taken from the male employees. The findings presented in *Tables 22a* and *22b*, suggest that the choice between actual and potential labour market experience does not have any notable impact on the estimated tenure effect on the male sample. However, for the female employees, the inclusion of actual, instead of potential, labour market experience appears to reduce the contribution of tenure.

2.4.3.4 Examination of Alternative Control Vectors

In this section I examine the robustness of my findings on tenure effect using alternative control vectors in the model estimated at the second stage of Topel's method. There are four different control vectors added to the *Basic Model*, identical to the ones employed in the previous sections of this chapter (*Models 2-5*). These five models are estimated separately for the male and female full-time employees, alternatively for the unbalanced and balanced sample. The method used for the construction of first difference in tenure and experience terms is *method 2*. In ***Tables 2.23*** and ***2.24*** the returns to 5, 10, 15 and 20 years of employer-tenure are presented, estimated on the de-trended nominal wages (AEI). For the male employees the tenure effect varies across the different control vectors used. The ten years effect of tenure ranges from 10 per cent (*Model 1*) to 19.2 per cent (*Model 4*) for the unbalanced sample, and for the balanced sample from 21 per cent (*Model 1*) to 34 per cent (*Model 4*). *Model 4* gives the highest estimates and *Model 1* the lowest ones in both samples. In addition, as already noted in the previous section, the estimated tenure effect is significantly higher on the balanced sample. For the female employees, the tenure effect of ten years does not exceed the 2 per cent when estimated on the unbalanced sample, and it is small and negative on the balanced sample.

The same process is repeated but this time instead of using the de-trended nominal wage I use the deflated one, based on the RPI. *Model 4* continues to give the highest returns to tenure and *Model 1* the lowest for the male employees. The estimates are noticeably higher for the balanced sample compared to the unbalanced. Furthermore, as probably expected from the previous analysis, the estimated returns to tenure presented in ***Table 2.25*** are larger compared to those in ***Table 2.23***. For the female employees (***Table 2.26***), the estimated returns to tenure have dramatically increased in all cases. Now the effect of ten years of employer-tenure ranges from 8.5 per cent (*Model 1*) to 12.5 per cent (*Models 4* and *5*) for the unbalanced sample and from 15 per cent (*Model 1*) to 19 per cent (*Model 3*) for the balanced sample. Contrary to the findings in the previous section, here the estimates are significantly larger when estimated on the balanced sample.

Finally the analysis described so far in this section is repeated this time though in the first-difference model used in the first step of Topel's 2-step method a cubic in tenure and a quadratic in potential experience is included as opposed to the 4th order polynomials in both tenure and experience used so far. ***Tables 2.27, 2.28, 2.29*** and ***2.30*** present the effect of 5, 10, 15 and 20 years of employer-tenure. In all the cases the estimated returns to tenure are reduced noticeably, with the only exception the case of female employees from the unbalanced sample, when the de-trended nominal wage is used.

Two main points can be drawn from the analysis, based on Topel's two-step method. The estimated tenure effect, on the male employees, is significantly higher compared with the one derived from both OLS and the instrumental variables technique. In addition, the computed returns to tenure are '*worryingly*' sensitive to the choice of time treatment for both male and female employees.

2.4.4 Panel Data Analysis on the Returns to Tenure

An alternative method of removing the endogeneity bias in the estimates of tenure effect, derived from the potential correlation between the tenure variable and the unobserved individual specific and job match characteristics, is the use of panel estimators. Consider a simple wage equation model given by:

$$W_{it} = \alpha + \beta T_{it} + v_i + \varepsilon_{it} \qquad (2.26)$$

In this model $v_i + \varepsilon_{it}$ is the residual, where ε_{it} has the usual properties, $\varepsilon_{it} \sim IID(0,\sigma^2)$, and v_i is the unit-specific residual, differing between units but staying constant for any particular unit over time. From equation (2.26) we can derive:

$$\overline{W}_i = \alpha + \beta \overline{T}_i + v_i + \overline{\varepsilon}_i \qquad (2.27)$$

where $\overline{Y_i}$, $\overline{T_i}$, $\overline{\varepsilon_i}$ are the means over time. Subtracting equation (2.27) from (2.26) we get:

$$\left(W_{it}-\overline{W_i}\right)=\beta\left(T_{it}-\overline{T_i}\right)+\left(\varepsilon_{it}-\overline{\varepsilon_i}\right) \tag{2.28}$$

The fixed effect (within group) estimator uses OLS to estimate equation (2.28) and with this way it subsumes the omitted variables (unobserved heterogeneity across units). On the other hand, the random effects (GLS) estimator provides a weighted average of the estimates produced by the between and within estimators. Equivalently, it estimates of the following model:

$$\left(W_{it}-\theta\overline{W_i}\right)=\left(1-\theta\right)\alpha+\beta\left(T_{it}-\theta\overline{T_i}\right)+\left[\left(1-\theta\right)v_i+\left(\varepsilon_{it}-\theta\overline{\varepsilon_i}\right)\right] \tag{2.29}$$

In the case of random effects estimator the random component takes account of the potential heterogeneity derived from the unobserved individual and job match characteristics. For the purpose of completeness in my analysis, I use both fixed effects (within group) and random effects estimators. The unit *i* in my estimates represent an individual working for a particular employer (*ij*). Therefore, I take different values when the same individual is observed working for a different employer in the sample. This way I may probably employ a better control for both individual and job match heterogeneity, since estimates are based on deviations of the variables from their individual means, specific to each particular employer-employee relationship.

An obvious question raised is which estimator is more appropriate to use on my panel sample. The answer is not a straightforward one. For that reason, I use the Hausman specification test (1978). The Hausman test, under the assumption of correct specification, tests the appropriateness of the random effects estimator applied to the data. The null hypothesis is that the fixed effects and random effects estimator are the same, i.e. the random effects ν_i and the regressors T_{it} are uncorrelated. While the fixed effects estimator is consistent under the null or alternative, the random effects estimator is consistent and efficient only under the null hypothesis. Therefore, rejection of the null hypothesis means that the random effects estimator is not consistent, implying the appropriateness of using the fixed effects estimator.

The use of FE estimator gives rise to a problem concerning the estimation of the returns to general labour market skills. In my analysis, I use the potential labour market experience (*PotExp*) of an individual as a proxy of his accumulated general labour market human capital. *PotExp* is defined as the difference between current age and the age the individual fist left full-time education, therefore we expect that it will increase by a year from wave to wave for all respondents irrespectively to their true employment status. However, in the estimated earnings models I include, alongside the other regressors (and *PotExp*), a time trend variable that increases by one unit each wave, in order to capture potential unobserved time effects. The inclusion of both the linear term of *PotExp* and of the time trend in the wage equation model makes their identification impossible when the FE estimator is employed, since they both increase by one (unit) each wave[14]. As a remedy to this identification problem, when I estimate the wage equation using FE, I exclude the linear term of *PotExp* and consider only its quadratic term. The estimate, in this case, of the time trend represents the joint effect of the linear term of *PotExp* and time trend peculiarities. Obviously, the downside of this solution is that we cannot distinguish these two effects, therefore we cannot precisely derive an estimate on the contribution of general labour market skills in the wage determination process. A similar problem arises when I consider actual labour market experience instead of

[14] The deviation from their mean $\left(E_{it} - \bar{E}_{t}\right)$ in each wave is exactly the same for both of them, making the identification of these two effects impossible.

potential experience. Since both employer-tenure and actual labour market experience increase by the same amount between waves, the estimation process based on FE makes the distinction of the effect of the linear terms of these two variables impossible. Therefore, one of these terms is dropped out of the estimated wage equation model. This basically results in obtaining an estimate that represents the joint and indistinguishable effect of the linear terms of tenure and actual working experience.

2.4.4.1 Random Effects and Fixed Effects Estimations on the Basic Model

Initially the *Basic Model* is estimated using both fixed effects (within group) and random effects estimators. The estimates on the male and female unbalanced sample are presented in *Table 2.31* and on the balanced sample in *Table 2.32*. The unbalanced sample random effects estimates show returns to ten years of tenure around 6 per cent for the male employees and 8 per cent for the female employees. When the model is estimated using the fixed effects estimator, the tenure effect is increased in both cases to 8 per cent and 12 per cent, respectively, with the effect for the female employees still significantly higher than the equivalent estimated on the male sample. The picture does not change dramatically when the *Basic Model* is estimated on the balanced panel sample, with the exception when the random effects estimator is used. In that case, the tenure effect of ten years on the log wage is slightly reduced to 4 per cent and 7 per cent for men and women, respectively. Finally, the Hausman test suggests that, for both group of employees, there is a systematic difference in the estimated coefficients from the two estimators. The performed test rejects the null hypothesis, implying that it may be better to use the fixed effects estimator for the study of tenure effect.

The analysis is repeated this time using the actual labour market experience instead of the potential. The results are presented in ***Tables 2.31*** and ***2.32***, second and forth column. Due to the identification problems related to the inclusion of actual labour market experience in the wage equation, in the fixed effect estimates I present only the obtained coefficients of tenure and experience. Although I cannot distinguish and calculate the tenure and experience effect, a comparison between the presented coefficients when actual instead of potential experience is considered can be quite informative of any notable changes in the tenure effect.

From the random effect estimates, on both unbalanced and balanced samples, it appears that the estimated tenure effect is only marginally affected by the inclusion of actual labour market experience for the male employees. On the contrary, the magnitude of tenure effect in the case of female employees is reduced, especially in the unbalanced sample estimates. Although I cannot explicitly derive the tenure effect for the fixed effect estimates, from an examination of the coefficients we can conclude that the estimates are quite robust and not really affected by the choice between actual or potential experience in the regressors vector.

The picture we get from the analysis so far is that, first of all, the contribution of employer-tenure on the wage determination is quite modest, with the returns to ten years of tenure not exceeding the 10 per cent in most of the cases, for both male and female employees. The calculated tenure effect is sensitive to the choice of estimator, with fixed effects estimator giving larger returns to tenure. Finally, the Hausman test strongly suggests that the random effect estimator is not consistent, implying that it may be more suitable to use the fixed effects estimator on the male and female panel samples.

2.4.4.2 Wage Treatment Over Time and Alternative Control Vectors

The next step in my analysis is to examine the sensitivity of the estimated returns to tenure to alternative wage treatment over time. The findings on the unbalanced and balanced samples are summarised in ***Tables 2.33*** and ***2.34***, respectively. Although there is some variation between the different methods of time treatment in the models, the results appear to be quite robust when a time trend is included, irrespective to whether nominal or real wages are used. For the male employees the random effects estimates give returns to ten years of tenure slightly below 6 per cent on the unbalanced sample, and around 4 per cent on the balanced. When the fixed effects estimator is employed the estimates increase to roughly 7.5 per cent for both panel samples. Similarly for the female employees, the random effects estimator suggests an equivalent effect of 8 per cent, when estimated on the unbalanced sample and approximately 7 per cent on the balanced sample. The equivalent estimates based on the fixed effects estimator are roughly 12 per cent and 11 per cent.

The last part of this section focuses on the inclusion of alternative control vectors in the *Basic Model* described above. The estimates are summarised and presented separately for the male and female full-time employees in ***Tables 2.35-2.38*** both from the unbalanced and balanced sample, using alternatively the random effect and fixed effect estimators. Although the derived returns to tenure appear to differ across the different control vectors used, no noticeable impact is occurred. The unbalanced panel sample estimates overall suggest that the returns to ten years of tenure do not exceed 8 per cent for the male employees and 11 per cent for the women. For the balanced sample the equivalent estimates are slightly reduced for the male employees giving a maximum effect of 7 per cent and for their female peers marginally increased, with a maximum ten-year tenure effect of 12 per cent.

Concluding the analysis based on panel estimators, three main points can be outlined. About the choice between the fixed effect and random effect estimator, the Hausman test suggests that it may be better to use the fixed effect estimator, since the null hypothesis is rejected in all the cases examined. Nevertheless, no matter which estimator is employed, the impact of employer-tenure is quite modest, with a ten-year tenure effect not larger than 10 per cent for both the male and female employees. The fact that the estimates based on the panel estimators do not differ a lot from the equivalent obtained from OLS may be an indication that endogeneity bias, derived from the potential dependence of the employer-tenure on components of the error term, is not after all an important issue for my data set.

2.4.5 Sensitivity to Outliers

The quantile regression over the median, or median regression, is quite similar to the standard OLS method. In the median regression the objective is to estimate the median of the dependent variable, conditional on the values of the independent variables, while the OLS estimates the mean of the dependent. The median regression can be thought as a method that finds a line through the data such that it minimises the sum of the absolute residuals, where in the case of the standard OLS it is the sum of the squares. Means and subsequently OLS are sensitive to outliers; therefore here I employ quantile regressions in an attempt to correct for any outlier-sensitivity deficiency in OLS.

For the purpose of my analysis, I estimate the five alternative wage equations (*Models 1-5*) and the results, based on the pooled sample, are presented separately for the whole sample, the male and the female employees in *Table 2.39*. These findings are directly comparable with those in *Table 2.5* where the standard OLS method is used. For the male sample, it appears that the tenure effect is noticeably reduced when estimated with median regressions, compared to OLS. The estimated returns to ten years of tenure range from 7.6 to 11 per cent when the OLS method is used, while in the case of median regression it ranges between 4.4 to 8 per cent. The median regressions reduce the estimated effect for the female employees in most of the cases as well, but here the reduction is not that large. While before the effect of ten years of tenure was between 6.4 and 12.9 per cent, now it varies between 7.1 and 11.5 per cent.

Further, the returns to tenure are examined under different methods of time treatment. The estimated tenure effect for both male and female full-time employees slightly varies across the different ways of wage treatment over time (*Table 2.40*). The ten years employer-tenure effect on log wages ranges from 5 to 7 per cent for male employees, and from 6.3 to 8.5 per cent for female. Comparing these findings with the least square estimates in *Table 2.6*, we see that for the male sample the contribution of tenure is decreased, while for female employees the picture is not so clear.

I also explore the impact that the inclusion of actual full-time experience, instead of potential experience, in the *Basic Model* may have on the estimated returns to tenure (*Table 2.41*). In the case of male employees the tenure effect marginally reduces when actual labour market experience is added to the regressors, but still appears to have a modest but significant effect. The exception is the estimates of the balanced sample where the derived effect is insignificant in both cases. For the female employees, the tenure effect reduces both in magnitude and significance when actual labour market experience is considered.

Finally, I re-estimate the five wage equation models presented in ***Table 2.39***, this time using robust regressions. In general, it is expected that the estimates between the quantile and the robust regressions will be quite similar, with smaller standard errors though in the latter. The estimates are presented in ***Table 2.42***. Comparing these results with the ones shown in ***Table 2.39***, we see that for both the male and female employees the estimated tenure effect is slightly increased in most cases. However, as expected, no dramatic change is occurred.

2.4.6 An Overview of the Findings on Tenure-Wage Growth

In the analysis presented above, I examine the contribution of employer-tenure to wage determination, while addressing the issue of potential heterogeneity bias in the estimates of interest. For that purpose, I employ alongside the standard least square, AS's instrumental variable technique, Topel's two-step method and panel estimators. Despite the fact that there is some variation in the derived tenure effect, across the different methods used, we can draw some conclusions on the impact tenure has on individuals' wage profiles.

The findings on the male full-time employees suggest that employer-tenure plays a rather limited role on an individual's earnings profiles. Overall, it appears that the contribution of ten years of employer-tenure, in a log linear wage equation, is slightly less than 10 per cent. Although throughout this chapter I employ various specifications regarding the earnings equation model (**Models 1-5**), my preferred specification is **Model 5**. This is the full specification model that includes various controls for both individual and workplace characteristics alongside the human capital variables of interest[15] (whereas Models 1-4 are all nested in Model 5). The estimates on this particular wage equation model suggest a ten-year tenure effect between 7.1 and 9.1 percent (fixed-effects and least squares respectively). The performed Hausman test between the AS instrumental variable estimates and standard least square estimates propose that endogeneity bias may after all not be an issue of concern (based on the particular instruments employed) for these data. Similar tests between a fixed-effects and a random-effects model are in favour of the former. Nevertheless, no matter which estimator is the preferred one (fixed-effects or OLS) what stands out from all these estimates is that employer-tenure has a statistical significant, positive but modest, in magnitude, contribution in the wage determination process. The only exception though is when Topel's two-step method is employed, where the estimated tenure effect appears to be quite significant and noticeably above the equivalent estimates obtained from the other techniques.

The picture is rather similar for the female full-time employees as well. The alternative methods employed suggest that employer-tenure can contribute only little in the *'jigsaw'* of wage determination. In particular, it is found that ten years of employer-tenure have an impact of around 10 per cent on the log of the wages based on my preferred estimator, the fixed-effects model. It is worth mentioning though that when the instrumental variables technique and Topel's method (based on de-trended nominal wages-AEI) are used, the estimates imply that there is no real tenure effect for the female employees.

---

[15] The regressors considered are a cubic polynomial in tenure, a quadratic polynomial in potential labour market experience, age left education, a time trend and dummy variables for individual's skills and qualifications, industry and occupation, region, establishment size and union coverage and membership.

2.5 Quantile Regressions

2.5.1 Introduction

My analysis so far is focused on the estimation of the returns to employer-tenure and the investigation of endogeneity bias, driven by unobserved individual characteristics and job-match characteristics, as addressed in the various techniques employed. The whole discussion above though is based on the assumption that there is a homogeneous tenure effect. In other words, I assume that observationally identical individuals, located at different points in the conditional wage distribution, are equally rewarded for their seniority and accumulated employer-specific skills. However, this approach, although commonly embraced in the literature, may be quite restrictive and not so enlightening on the true contribution of employer-tenure on earnings profiles. "*'On the average' has never been a satisfactory statement with which to conclude a study on heterogeneous populations. Characterization of the conditional mean constitutes only a limited aspect of possibly more extensive changes involving the entire distribution.*" (Buchinsky 1994, pp. 453).

Here, I challenge the assumption of a uniform tenure effect, and investigate whether the returns to employer-tenure differ across the conditional wage distribution. For the examination of heterogeneity in the returns to tenure I employ the quantile regression technique. Quantile regressions allow us to explore the contribution of tenure on wages at different points (quantiles) of the conditional distribution of wages, instead of restricting our analysis on the average treatment effects of employer-tenure. Any difference in the estimated tenure effect across the quantiles will simply suggest that the decision of observationally identical individuals to work for one more year with their current employer will not have the same effect on their wages. The analysis is outlined as follows.

In *Section 2.5.2*, I briefly describe the quantile regression model and present the main estimates on the returns to tenure. Formal tests for heterogeneity are employed in *Section 2.5.3*. The potential endogeneity bias in the estimates of interest is addressed in *Section 2.5.4*, where I adopt the instrumental variables approach in the quantile regressions framework. Finally, in *Section 2.5.5*, I conclude the discussion with the main findings.

2.5.2 Quantile Regression Models

2.5.2.1 Fundamentals of Quantile Regression

Koenker and Bassett (1978a) first introduced the quantile regression model or the '*regression quantiles*' as they baptised them. This new class of statistics for the linear model has analogous properties to the ordinary sample quantiles of the location model. The notion of a simple maximisation problem yielding the ordinary sample quantiles in the location model is extended to a more general class of linear models in which the conditional quantiles have a linear form. Although quantile regression models were introduced at the end of the 1970's, it was not until the beginning of 1990's that researchers began to utilise this new '*tool*', helped by the recent developments in the techniques of quantile regression (Powell, 1983, 1984 and 1986; Buchinsky, 1995).

Quantile regression enables the researcher to have a complete view of the statistical landscape and the relationships among stochastic variables. Specifically, the main features/advantages of quantile regression models are as follows: (a) they can be used to characterise the entire conditional distribution of the dependent variable given a set of regressors; (b) they allow the researcher to focus on quantile treatment effects rather than on average treatment effects, i.e. different solutions at distinct quantiles may be interpreted as differences in the response of the dependent variable to changes in the regressors at various points in the conditional distribution of the dependent variable; (c) when we cannot assume that the error term is normally distributed, quantile regression estimators may be more efficient than least squares estimators; (d) the estimated coefficient vector is not sensitive to outlier observations on the dependent variable, since the quantile regression objective function is a weighted sum of absolute deviations, which gives a robust measure of location and finally; (e) their linear programming representation (LP) makes estimation relatively easy.

Here, I employ simple quantile regression techniques in order to examine the magnitude of the employer-tenure effect across the conditional distribution of wages. The framework of my analysis can be described by a log linear wage equation model, where employer-tenure is included in the regressors vector:

$$W_{ijt} = \beta X_{ijt} + u_{ijt} \tag{2.30}$$

where *ijt* represents the individual *i* at a particular job *j* at period/time *t* and X_{ijt} is the regressors vector. For simplicity reasons we can rewrite the model as:

$$W_i = \beta X_i + u_i \tag{2.31}$$

Then the quantile regression model is given as (Buchinsky (1994)):

$$W_i = X_i'\beta_\theta + u_{\theta i}\ , \quad Quant_\theta\left(W_i \mid X_i\right) = X_i'\beta_\theta \tag{2.32}$$

where $Quant_\theta\left(W_i \mid X_i\right)$ denotes the θ^{th} conditional quantile, $0 < \theta < 1$, of the dependent variable, W_i, given the regressors vector, X_i. The estimated vector of parameters is the solution of a simple minimasation problem defined as:

$$\begin{aligned}&\min_{\beta\in R^k}\left\{\sum_{i:\ln w_i\geq x_i'\beta}\theta\left|W_i-X_i\beta_\theta\right|+\sum_{i:\ln w_i<x_i'\beta}(1-\theta)\left|W_i-X_i\beta_\theta\right|\right\}\\&=\min_{\beta\in R^k}\sum_{i=1}\rho_\theta\left(W_i-X_i\beta_\theta\right)\end{aligned}\qquad(2.33)$$

where β_θ is the vector of the estimated coefficients of the regressors at the θ^{th} conditional quantile. Quantile regressions estimated at different values of θ provide a family of returns to tenure. Variation in the estimated contribution of tenure across the quantiles of the conditional distribution of wages may be an indication of heterogeneous returns to tenure. For this reason in the analysis that follows I estimate a log linear wage equation model at different quantiles, in particular θ=.1, .2, .3, ..., .9 quantile, and examine whether the contribution of employer-tenure on wages has the same magnitude or not across the whole wage distribution.

2.5.2.2 The Empirical Analysis

The *Basic Model* is estimated on the pooled sample and the returns to ten years of employer-tenure are calculated and presented in ***Table 2.43*** with the standard errors[16] reported in parentheses. The first half of the table refers to male full-time employees and the second half to female. Examining the employer-tenure effect across the conditional distribution of the log hourly wage for the male employees we can clearly see that the effect varies along the quantiles. To be more specific, there is

[16] When errors are not independently and identically distributed it appears that calculated standard errors are underestimated. A bootstrapped estimate of the entire variance-covariance matrix of the estimators would be more accurate in that case. However, such a method requires lengthy computation time. In addition, since the dependent variable in the estimated models is in log, it is expected that standard errors, estimated by both methods, will be identical.

a sharp and monotonic decline in the tenure effect up to the .4 quantile. While the estimated returns to ten years of tenure at the .1 quantile are slightly less than 20 per cent, the same years of tenure appear to contribute significantly less at the .4 quantile where the effect is estimated to be 7 per cent. For the rest of the quantiles there appears to be only a relatively modest decline as θ increases from .4 to .9, where one traces the entire distribution of the log hourly wage conditional on the vector of regressors. The estimated effect of ten years of employer-tenure at the .9 quantile is 4 per cent, marginally lower than the one obtained from the median regression $(\theta = 5)$, where the effect is 6 per cent. For illustration reasons the estimates are plotted and presented in ***Figure 2.1a***, where one can clearly see how the tenure effect varies across the conditional distribution of the log hourly wage. The 95 per cent confidence interval is depicted as well in the figure.

It is worth mentioning that simple OLS estimate of this model gives returns to ten years of tenure around 9.5 per cent. Comparing the OLS estimate with the quantile regression model it is apparent that there is a significant value added in my analysis when using the second technique. The fact that the contribution of employer-tenure in the estimated wage equation model fluctuates across the quantiles of the conditional distribution, warns us that maybe an estimated uniform tenure effect, obtained from a simple OLS, is not sufficient to describe the whole picture. It appears that the employer-tenure effect has a different significance at various points of the wage distribution and restricting our analysis to the estimation of a uniform effect does not allow us to see the whole picture, the true contribution of employer-tenure on wages. This means that the returns to tenure do not appear to be homogeneous across various points of the wage distribution or, in other words any increase in tenure does not necessarily has a similar effect on wages of observationally identical individuals. Furthermore, looking at the difference between two consecutive conditional quantiles it appears that the tenure effect decreases monotonically at the lower part of the wage distribution, followed by a rather flat rate.

The results presented above can be interpreted in various ways depending on our perspective on the conditional wage distribution. One may view the wage distribution as reflecting the distribution of unobserved '*ability*', where low ability workers are those located to the left end of the wage distribution and high ability workers those located further to the right. '*Ability*' here refers to individual's initial endowments of human capital that although they are unobservable, they are still marketable and translated into higher earnings. In this framework, one way of interpreting the findings is that employer-tenure contributes relatively more to low ability individuals, in other words it appears that seniority compensates more the less able for their '*less favorable genetic endowments*'. Alternatively one can say that employer-tenure appears to contribute more in '*low paying*' jobs (lower quantiles) rather than in '*high paying*' jobs (upper quantiles). What this means is that seniority plays an important role in the wage determination in '*low paying*' jobs, i.e. in jobs where most likely no specific skills or high skills are required. This may be the case for instance due to the existence of particular seniority rules in the firm, or because of a strong presence of trade unions in the workplace. However, this is not the case for the '*high paying*' jobs, usually jobs that require high skilled and well-educated employees. Maybe in these jobs other factors, like productivity, have a more important role than employer-tenure or there are no particular promotion policies related to seniority in these firms. In addition, the findings have some very interesting implications concerning wage inequality, which here can be thought as the difference between two conditional quantiles. The declining returns to tenure, as we consider higher quantiles, imply that tenure contributes negatively to wage inequality. In other words, seniority and accumulated employer-specific skills appear to decrease wage dispersion, a finding of great interest if one considers the increasing wage inequality in the British labour market of the 1990s.

The wage equation model is also estimated for the female employees and the returns to ten years of employer-tenure are summarised in ***Table 2.43***, in the second half of the first column. Despite some fluctuations in the estimates across the quantiles of the conditional distribution, it appears that the employer-tenure effect is fairly uniform across the whole distribution, apart from the lowest part of the wage distribution $(\theta = 1)$ where the estimated effect is way below the rest of the estimates (roughly 1 per cent) and appears to be statistically insignificant. According to the findings, ten years of employer-tenure contribute to the log hourly wage of a female full-time employee by 6 to 8 per cent. The above estimates are plotted in ***Figure 2.2a*** along with the 95 per cent confidence interval. One can clearly see that the depicted line is almost a straight horizontal line.

The estimated employer-tenure effect at the mean, obtained from simple OLS, does not differ a lot from the previous findings. In particular, it seems that ten years of tenure have a positive effect of 6.4 per cent on the log hourly wage. The main conclusion from these estimates is that tenure effect is quite uniform across different points of the wage distribution, suggesting that seniority is equally rewarded among female workers. The choice of using quantile regression techniques instead of OLS does not provide us with any extra piece of information, in the case of women. The estimated ten years tenure effect is positive but quite modest and all cases is less than 10 per cent. In terms of wage inequality, employer-tenure does not appear to have any positive or negative impact upon inequality.

The analysis is repeated again; three different earnings equations are estimated, with different covariates included in the regressors vector (*Models 2, 3 and 5*)[17]. The returns to ten years of employer-tenure are presented in ***Table 2.43*** (columns 2-4) and, for illustration reasons, the estimated effects are plotted in ***Figures 2.1b-d*** and ***2.2b-d*** for men and women respectively, alongside the 95 per cent confidence interval.

From ***Table 2.43*** we can see that the picture does not change dramatically. For the male employees the pattern is the same, with a sharp and monotonic decline in the estimated returns to ten years of tenure, up to the .4 quantile, followed by a modest decline across the rest of the conditional quantiles. In the case of female employees, the only difference occurred is that the ten years tenure effect estimated at the .1 quantile has been '*corrected*' and now it is at a similar level with the estimates at the rest of the quantiles. Similar to *Model 1* estimates, the ten years tenure effect appears to be fairly uniform across the quantiles of the conditional wage distribution, probably with *Model 3* the only exception, where at .8 and .9 quantiles the estimated tenure effect drops quite a lot.

Although the findings are quite robust no matter which specification is used, for both male and female employees, the level of the calculated effect slightly changes. In order to see that clearly I plotted the estimated ten-year employer-tenure effect obtained from the four different models in two diagrams, ***Figures 2.3*** & ***2.4*** for men and women respectively. From ***Figure 2.3***, we can see that there is some various in the estimated effect across the four different models used. *Model 3*, appears to give the highest estimates at all conditional quantiles, while *Model 2* gives the lowest tenure effect at almost all the quantiles estimated. Nevertheless, the difference in the

[17] *Model 4* is excluded as the findings from this model are almost identical with those from *Model 5*.

ten-year tenure effect between the four models, estimated at the same quantile, does not seem to exceed the 5 per cent in any of the cases. In addition the estimates appear to converge at the lower and the upper part of the wage distribution, while the largest differences occur around the median of the distribution. In ***Figure 2.4***, female full-time employees, the lines plotted appear to be roughly parallel to each other, denoting that the pattern is similar irrespectively to which model is used but that the magnitude of the estimated effect varies. *Model 1* provides the lowest estimates across all the quantiles, while *Model 4* gives the highest returns to ten years of tenure at almost all the quantiles estimated. Even though the returns to ten years of employer-tenure fluctuate between 6 per cent and 13 per cent, the impact of tenure on wages remains quite modest in all cases.

A final comment on the discussion presented here and particularly on the figures provided. It would be interesting to plot together the estimated returns to tenure for both male and female employees and do a comparison in order to deduce some conclusions on gender wage differentials. However, this probably would not be accurate since the quantile points are quite different between male and female employees. What this means is that we cannot directly compare the contribution of employer-tenure in the wage determination between male and female employees because the jobs for example included in a particular quantile of the wage distribution are very different between the two samples. In other words it is not correct to infer that, for example, in '*high paying*' jobs seniority is more appreciated in the case of female employees compare to male employees. The reason is that these '*high paying*' jobs are not the same or necessarily available to both samples.

2.5.3 Heterogeneity in Employer-Tenure

2.5.3.1 A Test for Heterogeneity

As it is already mentioned above, if there appears to be variation in the contribution of tenure across the quantiles of the conditional distribution, then this can be interpreted as evidence of existence of heterogeneity in the returns to tenure. The analysis in the previous section suggests that at least for the male employees seniority and accumulated employer-specific skills are more important in the earnings profiles of those located at the left tail of the conditional wage distribution. A formal way to test for heterogeneity, i.e. examine whether there is statistically significant variation, is by performing test of equality on the estimated tenure effect between different quantiles.

In order to understand the basic principle (Koenker and Bassett, 1982) behind the methodology used to test for heterogeneity, let's assume a random variable *Y*, with c.d.f. $F(y|x)$, depending upon a row vector of exogenous variables *x*, where $x_{i1} = 1$ for all *i* (i.e. the first component of *x* is an intercept). Then the conditional quantile function of *Y*, as a linear function of *x*, can be written as:

$$Q_y(u|x) = \sum_{k=1}^{K} x_k \beta_k(u) = x\beta(u) \tag{2.34}$$

where the vector of contants $\beta(u)$ depends upon *u*. Now if we assume that the errors are independently and identically distributed we can re-write equation (2.34) as

$$Q_y(u|x) = x\beta + Q_\varepsilon(u) \tag{2.35}$$

with β the (fixed) vector of parameters and $Q_\varepsilon(u)$ the quantile function of the error distribution. Therefore in the case of *i.i.d.* errors:

$$\beta(u) = \beta + (Q_\varepsilon(u), 0 \ldots, 0)' \tag{2.36}$$

What this means is that we can depict the conditional quantile functions as a family of parallel hyperplanes, with the slope parameters β identical at every quantile. In other words, the exogenous variables influence only the location of the conditional distribution $F(y \mid x)$, but not the shape. However, if we relax the assumption of *i.i.d* errors then the slope coefficients depend, in a nontrivial way, on *u*. Consequently, the exogenous variables may influence several characteristics (like the shape and the tail behaviour) of the conditional distribution of *Y*. Based on this framework outlined here, in the next section I test for the existence of heterogeneity in the estimated returns to employer-tenure.

2.5.3.2 The Findings

According to the classical theory of linear regression, the conditional quantile functions of the response variable *Y*, given the vector of regressors *X*, are all parallel to one another. What this means is that slope coefficients estimated at distinct quantiles of the conditional distribution should all be identical (homogeneous effect). To adopt this into the framework of my analysis, we can say that the estimated employer-tenure effect should be of the same magnitude across the quantiles. Recall ***Figures 2.1a-d & 2.2.a-d***, where the estimated returns to ten years of tenure are plotted across the quantiles, alongside the 95 per cent confidence interval band. Homogeneity in the returns to tenure would imply that these plotted lines are flat so that is possible to draw a horizontal line within the confidence interval band. An examination of curvature of the figures suggests the existence of heterogeneity in the returns to employer-tenure only for the sample of male employees though.

A method to formally test the presence of heterogeneity bias in the returns to tenure is to test the equality of the quantile slope coefficients. In practice what I do is test whether the observed differences along the estimated coefficients are statistically significant across quantiles. These tests of equality, introduced by Buchinsky (1995), are based on the bootstrap. The logic behind the bootstrap is the following. All measures of precision come from a statistic's sampling distribution, which in turn is determined by the distribution of the population. Since population distribution is unknown in most of the cases, bootstrapping technique assumes that the observed distribution is a good proxy of the population distribution. Then a number of samples are drawn from the (X_i, Y_i) initial sample (the size of these samples does not necessarily need to be equal to the size of the initial sample). For each of these samples drawn an estimator of the parameters vector, β_θ, is computed. Based on these replications we obtain the estimates of interest.

Continuing now to my analysis, I perform tests of equality of the returns to employer-tenure between different quantiles. More specifically, I test whether there is any significant difference in the ten-year tenure effect among the estimated quantiles. Bootstraping is a technique computationally demanding, therefore I have restricted the number of replications to twenty. Four alternative vectors of regressors are included in the estimated wage equation model same as the ones used in the previous section (*Models 1-3* and *5*) and the models are estimated separately for men and women. The results (p-value) computed from these tests are reported in ***Table 2.44***, where the first half of the table refers to male and the second one to the female employees. The tests confirm the visual impression.

For the male employees, the results imply the presence of heterogeneity bias in the estimated tenure effect, but only at the lower quantiles of the wage distribution. The tests of equality on the returns to tenure between the low quantiles and the middle quantiles and between the low quantiles and the high quantiles reject the null hypothesis of homogeneity. For instance, there is a statistical significant difference in the estimated tenure effect between the .10 quantile and the median, computed p-value is practically zero for all the alternative group of covariates used. The results presented for the male employees appear to be quite robust across the different regressors vectors used. For the female employees, the tests verify the impression we get from the figures. In almost all the cases, p-value is sufficiently high that the hypothesis of homogeneity cannot be rejected even at a 10 per cent level of significance, implying that the returns to tenure are of the same magnitude among female employees, located at different points of the wage distribution. Similar with the estimates for the male employees, the results do not appear to be sensitive to the choice of covariates in the wage equation model.

So far in my analysis based on the quantile regressions I did not attempt to control for potential endogeneity bias. Any observed difference in the estimated tenure effect at different points of the wage distribution is interpreted as evidence of heterogeneous returns to employer-tenure. However, this heterogeneity bias may be the outcome of potential correlation between tenure and unobserved individual characteristics and job-match effects. This issue is raised in the following section, where controls for potential endogeneity bias are employed in the quantile regression framework.

2.5.4 Two Stage Quantile Regression

The endogeneity bias issue addressed in previous sections of this chapter also appears to be a problem when using quantile regression. Just as OLS delivers inconsistent estimates when some of the explanatory variables are determined simultaneously with the dependent variable, quantile regression estimators suffer from similar endogeneity bias, due to the dependence between some of the regressors and the error term. Lets consider a structural equation (Powel, 1983):

$$Y = Y_1\gamma + X_1\beta + u \tag{2.37}$$

where Y is the response variable, Y_1 is a $n \times g$ matrix of endogeneous variables determined simultaneously with Y (in my analysis, employer-tenure), γ is the vector of the associated coefficients and X_1 is a $n \times k_1$ matrix of exogenous variables. One way to control for endogeneity bias in a model like the one given in equation (2.37) is to use some appropriate instrumental variables for Y_1 that are not correlated with the error term (u). Assuming that there exists X_2, a $n \times k_2$ matrix of instrumental variables, absent from equation (2.37), then we can employ an instrumental variables quantile regression estimator, in order to control for endogeneity bias. The application of instrumental variables technique in a quantile regression framework can be given in a two-stage interpretation. In the first stage, the explanatory variables are projected on the space spanned by the instruments:

$$Y_1 = X\Pi + v \tag{2.38}$$

where $X = [X_1, X_2]$ is a $n \times (k_1 + k_2)$ matrix collecting all the exogenous variables and ν is a vector of *i.i.d.* error terms. In the second stage, quantile regression of the response variable is performed on the projections obtained in the previous stage. Hence, the two-stage quantile regression (2SQR) estimator is the solution to the minimisation problem (2.33) as stated in Koenker and Bassett (1978) for the model specified in (2.37), where Y_1 is replaced by its first-stage OLS[18] estimates obtained from (2.38).

Here, for the purpose of my analysis I employ the AS instrumental variable[19] in the 2SQR framework, in order to examine whether the heterogeneity observed in the estimated tenure effect across the wage distribution is the result of endogeneity bias or not. Therefore, based on OLS estimator, employer-tenure (Y_1, using the notation above) is regressed on the instrumental variables (X_2) and on the vector of exogenous (predetermined) variables (X_1). In the second stage, quantile regressions on the wage equation model (2.32) are estimated, where the predicted values on tenure (Y_1) obtained from the first-stage estimations and the vector of exogenous variables (X_1) compose the control vector in the right-hand side of the model. Similar to the analysis followed in ***Section 2.5.2.2***, a wage equation model with four alternative groups of (predetermined) covariates (X_1) is estimated at several points of the conditional wage distribution.

The choice of AS's instrumental variables may raise some concern though. Previously, I replicated AS approach on the contribution of employer-tenure in a

18 Kim and Muller (2000) argue that the 2SQR estimator based on OLS prediction is potentially better, compared with a 2SQR estimator based on quantile prediction, when we are interested in only slope parameters.

19 Arias et al. (2001) underline that using differenced data on quantile regression is problematic, since differencing in the quantile regression context is not equivalent to a fixed effect estimator. In quantile regression, the order of the individuals matters, hence quantiles of the sum of two random variables are not equal to the sum of the quantiles of each random variable. However, there is no evidence that using the AS IV, where employer-tenure is instrumented with its deviation from individual mean for each employer, will raise similar problems as in the case of differenced data.

wage equation model (*Section 2.4.2*). The performed Hausman test, in the case of male employees, suggests that endogeneity bias is not present in the estimates of interest. Based on this result, and consequently on the chosen instruments, one could argue that the observed heterogeneity in the tenure effect across the quantiles is not the outcome of varying endogeneity bias in these estimates, for the male sample. For the case of female employees, the Hausman test on the contrary implies that endogeneity bias is present. However, the estimated employer-tenure effect across the wage distribution, based on the quantile regressions, appears to be rather flat and homogeneous. Therefore, we suspect that even though employer-tenure may be correlated with unobserved individual and workplace characteristics, its estimated effect across the quantiles probably will not change dramatically when employing the instrumental variables. Nevertheless, I believe that it is of great interest to apply the IV technique into the quantile regression framework and examine whether the picture remains unchanged or not for both male and female employees.

According to the estimates obtained, the employer-tenure effect of ten years is calculated and presented in *Table 2.45*, with the standard errors into parentheses. We can compare these estimates based on 2SQR with the results from the quantile regression estimator in *Table 2.43*. The adoption of IV techniques in the quantile regression framework slightly alters the estimates, however the overall picture remains fairly similar. One point that should be mentioned though is that for the first three models the derived tenure effect appears to be statistically significant only at the lower quantiles. The only exception is the last model, where employer-tenure is estimated to have a significant contribution at almost all points of the wage distribution considered. The derived ten-year tenure effect in this model still appears to be higher at the lower quantiles, followed by a flat rate at the mid and upper part of the wage distribution. For illustration reasons the estimates from *Table*

2.45 are plotted in *Figures 2.5a-d* and *2.6a-d*, along those from *Table 2.43*. Despite the variation in the findings between the two estimators, we can draw the same conclusion in both cases. There is heterogeneity in the returns to tenure across the wage distribution. Furthermore, based on the AS instruments, this observed heterogeneity cannot be attributed to the existence of potential (varying across the quantiles) correlation of employer-tenure with unobservable individual and workplace characteristics.

In order to get a more accurate picture of whether there is heterogeneity in the returns to tenure or not in the latter model, tests of equality of the quantile slope coefficients are performed, similar to the analysis followed in *Section 2.5.3*, based now on the 2SQR estimator. The p-values from the performed tests are summarised in *Table 2.46*, where one can see whether the estimated tenure effect varies significantly across different quantiles of the wage distribution, after controlling for potential endogeneity bias. The findings suggest that indeed there is significant variation in the estimated tenure effect between the lower quantiles and the mid and upper part of the wage distribution, providing further support to the discussion above.

The same analysis is conducted for the female employees and the findings are summarised in the second part of *Tables 2.45* and *2.46*. The use of 2SQR estimator reduces notably the magnitude of the derived ten-year tenure effect, particularly in the first two models where the effect appears to be negative at most quantiles examined. More importantly though, the contribution of tenure is estimated to be statistically insignificant, in all models examined, across the whole wage distribution. This last finding is similar to the one in *Section 2.4.2* where I use the AS IV technique as an alternative to OLS in order to control for endogeneity bias in the estimates of interest. Based on the IV approach, employer-tenure again does not appear to have any significant contribution in the wage determination process. Overall, employer-tenure is estimated to have a reduced (compared to ***Table 2.43***) and uniform effect across the whole wage distribution that does not appear to be statistically significant though.

In this section I examined whether potential endogeneity bias is the driving force behind any observed difference in the returns to tenure, estimated at various points of the wage distribution. The analysis, based on the 2SQR estimator and the particular AS instruments, for the male employees sample suggests that there is actual variation in the contribution of tenure between the lower and the mid and upper quantiles of the wage distribution. I do not find sufficient evidence to support the idea that the observed heterogeneity in the returns to tenure can actual be explained by possible correlation between employer-tenure and unobservable individual and workplace characteristics. A similar examination on the female employees does not provide any further insight to my discussion in the previous section (***Table 2.43***). Employer-tenure is calculated to have a flat effect across the whole wage distribution as before, although now it does not seem to have any statistical significance.

2.5.5 Conclusion

Here I challenged the assumption, almost universally adopted in the literature, that observationally identical individuals are equally rewarded for their seniority and employer-specific skills. The quantile regression estimator allow us to differentiate the contribution of tenure along the wage distribution, and focus on quantile treatment effects rather than on average treatment effects, as most of the studies in the literature do. Earnings equation models are therefore estimated at various quantiles of the wage distribution and an analysis is carried out on the estimated ten-year effect of employer-tenure. The main findings of this study suggest that, in the case of male employees, the contribution of tenure is not uniform. In particular, the estimated effect is significantly larger at the lower quantiles of the wage distribution while at the middle and upper end of the conditional distribution there is only a modest effect of around 5 to 7 per cent. On the other hand, for the female employees the returns to tenure appear to be quite similar at the various quantiles estimated, with the computed employer-tenure effect not exceeding the 10 to 12 per cent in most of the cases.

Furthermore, tests for heterogeneity support the visual impression we get from the figures presented. Heterogeneity does not appear to be an issue in the case of female employees, where there is an almost uniform tenure effect across the estimated quantiles. For the male employees, the results imply the presence of heterogeneity in the contribution of employer-tenure in wages, but only between the lower quantiles and the rest of the wage distribution. In addition, this observed variation in the contribution of tenure cannot be attributed to potential endogeneity bias in these estimates of interest. Even when I control for the likely correlation of employer-tenure with unobservable characteristics, the heterogeneity of tenure effect between the lower part and the rest of the wage distribution is still present.

2.6 Some Concluding Comments

The effect of employer-tenure on individuals' earnings profiles is a popular topic in labour economics. The understanding of the contribution of tenure to wages can provide us with some insights into the evolution of life-cycle earnings, as well as on job mobility issues. Furthermore, the investigation of the sources of wage growth can be quite informative to policy makers on issues like unemployment, training, pensions and other topics related to wage determination and individual's employability. It is well documented in the literature that conventional OLS estimates on tenure effect may overestimate the tenure effect due to heterogeneity bias driven by the correlation of employer-tenure with unobserved individual and job characteristics. Individuals with high unobserved ability are more likely to experience lengthy and less interrupted employment spells, while high-paying jobs are likely to survive more. Researchers have suggested various techniques that could potentially control for the heterogeneity bias in the estimates of interest. However, despite the several studies in the literature there is still controversy on the estimates of the true contribution of tenure.

In this chapter, I examine the returns to employer-tenure, exploring some of the methods suggested in the literature. Specifically alongside OLS, I employ the instrumental variable approach of AS (1987), the two-step method of Topel (1991) and both random effect and fixed effect panel estimators and assess the sensitivity of my findings to various specifications. In spite of the slight variation in the presented estimates, almost universally they all converge to the same conclusion. The true contribution of employer-tenure on wage growth appears to be rather modest. The estimated tenure effect for the male employees is below 10 per cent (ten-year effect), while for their female peers it is around 10 per cent. Overall, these findings clearly imply that tenure can explain only a small part of the variation in wages.

However, this analysis is based on average treatment effects and may not fully describe the true contribution of tenure.

In the last part of this chapter, I address the question of whether observationally identical individuals are equally rewarded for their seniority and examine the returns to tenure at several points of the wage distribution. In other words, as an alternative to an average tenure effect, I provide a group of estimates on tenure effect that correspond to different quantiles of the wage distribution. This way, I opt to obtain a more accurate and complete picture of the relationship between tenure and wage growth. The analysis, based on quantile regressions, suggests some rather interesting findings. While for the female employees, the tenure-earnings profiles can be described by a flat line plot across the distribution (with the estimated ten-year tenure effect between 10 and 12 per cent), there is considerable heterogeneity in the returns to tenure for the male employees. In particular, the estimated tenure effect appears to be significantly higher at the lower part of the wage distribution, compared to the mid and upper quantiles. The interpretation of this result depends strongly on how one views and understands the wage distribution, and hence may be open to alternative explanations. Nevertheless, I think this is an important finding that could guide future research on tenure effects to new directions.

Chapter 2: Tables

Table 2.1

OLS Estimates on Tenure Effect					
	Model 1	Model 2	Model 3	Model 4	Model 5
Pooled					
Ten/10	.056	.065	.086	.088	.084
	(.015)	(.014)	(.014)	(.013)	(.013)
$Ten^2/10^2$	-.009	-.012	-.013	-.017	-.017
	(.005)	(.005)	(.005)	(.005)	(.005)
Exp	.033	.030	.031	.028	.028
	(.001)	(.001)	(.001)	(.001)	(.001)
Exp^2	-5.964e-4	-5.488e-4	-5.71e-4	-5.053e-4	-4.990e-4
	(2.94e-5)	(2.74e-5)	(2.79e-5)	(2.62e-5)	(2.61e-5)
Adj. R^2	.361	.459	.447	.514	.517
Sample	13036				
T5	.026	.029	.040	.040	.038
	(.006)	(.006)	(.006)	(.006)	(.006)
T10	.047	.052	.073	.072	.067
	(.010)	(.010)	(.010)	(.009)	(.009)
T15	.064	.069	.100	.095	.088
	(.013)	(.012)	(.012)	(.011)	(.011)
T20	.077	.080	.121	.110	.101
	(.014)	(.013)	(.013)	(.012)	(.012)
Male					
Ten/10	.076	.059	.086	.071	.066
	(.018)	(.016)	(.017)	(.016)	(.016)
$Ten^2/10^2$	-.019	-.013	-.017	-.014	-.014
	(.006)	(.006)	(.006)	(.005)	(.005)
Exp	.037	.033	.036	.031	.031
	(.002)	(.002)	(.002)	(.002)	(.002)
Exp^2	-6.195e-4	-5.669e-4	-5.21e-4	-5.144e-4	-5.081e-4
	(3.66e-5)	(3.42e-5)	(3.55e-5)	(3.36e-5)	(3.35e-5)
Adj. R^2	.415	.504	.470	.533	.535
Sample	7638				
T5	.033	.026	.039	.032	.029
	(.007)	(.007)	(.007)	(.007)	(.007)
T10	.057	.046	.069	.056	.052
	(.012)	(.012)	(.012)	(.011)	(.011)
T15	.072	.059	.091	.074	.067
	(.015)	(.014)	(.015)	(.014)	(.014)
T20	.077	.066	.104	.084	.076
	(.016)	(.015)	(.016)	(.015)	(.015)
Female					
Ten/10	.036	.081	.096	.119	.119
	(.026)	(.024)	(.023)	(.022)	(.022)
$Ten^2/10^2$	-.021	-.038	-.035	-.043	-.045
	(.010)	(.009)	(.009)	(.009)	(.009)
Exp	.027	.026	.022	.022	.022
	(.002)	(.002)	(.002)	(.002)	(.002)
Exp^2	-5.334e-4	-5.095e-4	-4.714e-4	-4.488e-4	-4.434e-4
	(4.46e-5)	(4.12e-5)	(4.02e-5)	(3.84e-5)	(3.82)
Adj. R^2	.355	.471	.509	.555	.559
Sample	5398				

(*Table 2.1* continued)					
T5	.013 (.011))	.031 (.010)	.039 (.010)	.049 (.009)	.048 (.009)
T10	.016 (.017)	.043 (.016)	.061 (.015)	.076 (.015)	.075 (.015)
T15	.008 (.020)	.036 (.019)	.065 (.018)	.082 (.017)	.079 (.017)
T20	-.010 (.022)	.009 (.020)	.052 (.020)	.066 (.019)	.060 (.019)

Notes: Standard errors presented in brackets. Model 1 includes: age left education, a quadratic in employer-tenure, a quadratic in potential labour market experience, dummies for individual's skills and a time trend (Basic Model). Model 2 is the Basic Model plus regional dummies, 1-digit industry dummies and establishment size dummies. Model 3 is the Basic Model plus regional, occupational and qualification dummies. Model 4 is Basic Model plus dummy variables for region, industry and occupation, establishment size and individual's qualifications. Model 5 is Model 4 plus union coverage and union membership dummies.

Table 2.2

OLS Tenure Effect Sensitivity to Functional Form					
Pooled	T5	T10	T15	T20	Adj. R^2
Basic Equation	.026 (.006)	.047 (.010)	.064 (.013)	.077 (.014)	.361
Basic Equation plus dummy variable for tenure greater or equal to 1 year	.015 (.007)	.029 (.012)	.042 (.014)	.055 (.015)	.361
Basic Equation plus dummy variable for tenure greater or equal to 6 months	.020 (.007)	.037 (.011)	.053 (.013)	.065 (.014)	.361
Basic Equation plus interaction term between age left education and potential labour market experience	.026 (.006)	.048 (.010)	.067 (.013)	.081 (.014)	.369
Basic Equation plus additional polynomials in tenure (3rd order)	.056 (.010)	.079 (.013)	.081 (.013)	.075 (.014)	.362
Basic Equation plus additional polynomials in tenure (3rd & 4th order)	.061 (.013)	.082 (.014)	.082 (.014)	.077 (.014)	.362

Notes: The basic model includes age individuals left education, a quadratic in employer tenure and potential experience, skills dummies and a time trend. The wage is in nominal terms. Standard errors presented in brackets.

Table 2.3

OLS Tenure Effect Sensitivity to Functional Form					
Male (Pooled Sample)	T5	T10	T15	T20	Adj. R^2
Basic Equation	.033 (.007)	.057 (.012)	.072 (.015)	.077 (.016)	.415
Basic Equation plus dummy variable for tenure greater or equal to 1 year	.026 (.008)	.045 (.014)	.057 (.017)	.062 (.018)	.416
Basic Equation plus dummy variable for tenure greater or equal to 6 months	.027 (.008)	.047 (.013)	.059 (.016)	.064 (.017)	.416
Basic Equation plus interaction term between age left education and potential labour market experience	.033 (.007)	.057 (.012)	.071 (.015)	.076 (.016)	.418
Basic Equation plus additional polynomials in tenure (3rd order)	.067 (.012)	.094 (.016)	.094 (.016)	.079 (.016)	.416
Basic Equation plus additional polynomials in tenure (3rd & 4th order)	.068 (.016)	.095 (.017)	.094 (.016)	.079 (.017)	.416

Notes: The basic model includes age individuals left education, a quadratic in employer tenure and potential experience, skills dummies and a time trend. The wage is in nominal terms. Standard errors presented in brackets.

Table 2.4

OLS Tenure Effect Sensitivity to Functional Form					
Female (Pooled Sample)	T5	T10	T15	T20	Adj. R^2
Basic Equation	.013 (.011)	.016 (.017)	.008 (.020)	-.010 (.022)	.355
Basic Equation plus dummy variable for tenure greater or equal to 1 year	-.007 (.012)	-.017 (.019)	-.030 (.023)	-.045 (.024)	.357
Basic Equation plus dummy variable for tenure greater or equal to 6 months	.005 (.011)	.003 (.018)	-.006 (.022)	-.023 (.023)	.355
Basic Equation plus interaction term between age left education and potential labour market experience	.017 (.011)	.025 (.017)	.023 (.022)	.012 (.022)	.379
Basic Equation plus additional polynomials in tenure (3rd order)	.069 (.016)	.064 (.020)	.019 (.020)	-.029 (.022)	.358
Basic Equation plus additional polynomials in tenure (3rd & 4th order)	.062 (.021)	.061 (.021)	.019 (.020)	-.034 (.025)	.358

Notes: The basic model includes age individuals left education, a quadratic in employer tenure and potential experience, skills dummies and a time trend. The wage is in nominal terms. Standard errors presented in brackets.

Table 2.5

OLS Estimates on Tenure Effect					
	Model 1	Model 2	Model 3	Model 4	Model 5
Pooled					
Ten/10	.156 (.028)	.158 (.026)	.213 (.026)	.216 (.025)	.217 (.025)
$Ten^2/10^2$	-.094 (.021)	-.092 (.020)	-.121 (.020)	-.126 (.019)	-.131 (.019)
$Ten^3/10^3$	.017 (.004)	.016 (.004)	.022 (.004)	.023 (.004)	.023 (.004)
Exp	.033 (.001)	.030 (.001)	.031 (.001)	.029 (.001)	.028 (.001)
Exp^2	-6.010e-4 (2.94e-5)	-5.539e-4 (2.74e-5)	-5.734e-4 (2.78e-5)	-5.121e-4 (2.62e-5)	-5.060e-4 (2.61e-5)
Adj. R^2	.362	.460	.448	.515	.518
T5	.056 (.010)	.058 (.009)	.079 (.009)	.079 (.009)	.079 (.009)
T10	.079 (.013)	.082 (.012)	.114 (.012)	.113 (.011)	.110 (.011)
T15	.081 (.013)	.085 (.012)	.121 (.012)	.116 (.012)	.111 (.012)
T20	.075 (.014)	.078 (.013)	.119 (.013)	.108 (.012)	.099 (.012)
Male (Pooled Sample)					
Ten/10	.184 (.034)	.145 (.031)	.206 (.032)	.183 (.030)	.179 (.030)
$Ten^2/10^2$	-.107 (.024)	-.083 (.022)	-.115 (.023)	-.106 (.022)	-.107 (.022)
$Ten^3/10^3$	.017 (.005)	.014 (.004)	.019 (.004)	.018 (.004)	.018 (.004)
Exp	.037 (.002)	.033 (.002)	.036 (.002)	.032 (.002)	.031 (.002)
Exp^2	-6.272e-4 (3.66e-5)	-5.738e-4 (3.42e-5)	-6.007e-4 (3.56e-5)	-5.232e-4 (3.36e-5)	-5.169e-4 (3.36e-5)
Adj. R^2	.416	.504	.471	.534	.536
T5	.067 (.012)	.053 (.011)	.077 (.011)	.067 (.011)	.065 (.011)
T10	.094 (.016)	.076 (.015)	.110 (.015)	.095 (.014)	.091 (.014)
T15	.094 (.016)	.077 (.015)	.116 (.016)	.097 (.015)	.091 (.015)
T20	.079 (.016)	.068 (.015)	.107 (.016)	.086 (.015)	.078 (.015)
Female (Pooled Sample)					
Ten/10	.235 (.050)	.274 (.045)	.295 (.044)	.327 (.042)	.339 (.042)
$Ten^2/10^2$	-.218 (.043)	-.230 (.039)	-.232 (.038)	-.248 (.036)	-.261 (.036)
$Ten^3/10^3$	.047 (.010)	.045 (.009)	.047 (.009)	.048 (.008)	.051 (.008)
Exp	.026 (.002)	.025 (.002)	.022 (.002)	.022 (.002)	.021 (.002)
Exp^2	-5.206e-4 (4.46e-5)	-4.979e-4 (4.12e-5)	-4.594e-4 (4.01e-5)	-4.368e-4 (3.83e-5)	-4.304e-4 (3.82e-5)
Adj. R^2	.358	.474	.512	.558	.562
T5	.069 (.016)	.085 (.015)	.095 (.014)	.107 (.014)	.110 (.014)
T10	.064 (.020)	.090 (.018)	.109 (.018)	.127 (.017)	.128 (.017)
T15	.019 (.020)	.047 (.019)	.077 (.018)	.095 (.017)	.092 (.017)

(*Table 2.5* continued)					
T20	-.029 (.022)	-.009 (.021)	.033 (.020)	.047 (.019)	.041 (.019)

Notes: Standard errors presented in brackets. Model 1 includes: age left education, a cubic in employer-tenure, a quadratic in potential labour market experience, dummies for individual's skills and a time trend (Basic Model). Model 2 is the Basic Model plus regional dummies, 1-digit industry dummies and establishment size dummies. Model 3 is the Basic Model plus regional, occupational and qualification dummies. Model 4 is Basic Model plus dummy variables for region, industry and occupation, establishment size and individual's qualifications. Model 5 is Model 4 plus union coverage and union membership dummies.

Table 2.6

OLS Tenure Effect Sensitivity to Wage Treatment Over Time

	T5	T10	T15	T20	Adj. R^2
Male (Pooled Sample)					
Time Trend	.067 (.012)	.094 (.016)	.094 (.016)	.079 (.016)	.416
Wave Dummies	.067 (.012)	.094 (.016)	.094 (.016)	.079 (.016)	.416
Real Wage (Retail Price Index)	.069 (.012)	.097 (.016)	.097 (.016)	.082 (.016)	.396
Real Wage (Retail Price Index) plus Time Trend	.067 (.012)	.094 (.016)	.094 (.016)	.079 (.016)	.396
Real Wage (Average Earnings Index)	.062 (.012)	.086 (.016)	.086 (.016)	.072 (.016)	.392
Real Wage (Average Earnings Index) plus Time Trend	.067 (.012)	.094 (.016)	.093 (.016)	.079 (.016)	.393
Female (Pooled Sample)					
Time Trend	.069 (.016)	.064 (.020)	.019 (.020)	-.028 (.022)	.358
Wave Dummies	.069 (.016)	.064 (.020)	.020 (.020)	-.029 (.022)	.358
Real Wage (Retail Price Index)	.088 (.016)	.089 (.020)	.044 (.020)	-.010 (.022)	.325
Real Wage (Retail Price Index) plus Time Trend	.068 (.016)	.063 (.020)	.019 (.020)	-.029 (.022)	.329
Real Wage (Average Earnings Index)	.075 (.016)	.071 (.019)	.027 (.020)	-.023 (.022)	.323
Real Wage (Average Earnings Index) plus Time Trend	.068 (.016)	.062 (.020)	.018 (.020)	-.030 (.022)	.323

Notes: Every model includes age left education, a cubic in employer tenure, a quadratic in potential labour market experience and dummies for skills. Standard errors presented in brackets.

Table 2.7

OLS Estimates: Actual and Potential Experience				
	Male		Female	
	Potential	Actual	Potential	Actual
Pooled				
Ten/10	.184 (.034)	.150 (.034)	.235 (.050)	.185 (.049)
$Ten^2/10^2$	-.107 (.024)	-.087 (.024)	-.218 (.043)	-.224 (.043)
$Ten^3/10^3$	.017 (.005)	.015 (.005)	.047 (.010)	.051 (.010)
Exp	.037 (.002)	.035 (.002)	.026 (.002)	.032 (.024)
Exp^2	-6.272e-4 (3.66e-5)	-6.050e-4 (3.71e-5)	-5.206e-4 (4.46e-5)	-6.285e-4 (6.47e-5)
Adj. R^2	.416	.414	.358	.369
Sample	7637	7637	5397	5397
T5	.067 (.012)	.055 (.012)	.069 (.016)	.043 (.016)
T10	.094 (.016)	.077 (.016)	.064 (.020)	.013 (.020)
T15	.094 (.016)	.077 (.016)	.019 (.020)	-.053 (.020)
T20	.079 (.016)	.067 (.017)	-.029 (.022)	-.117 (.023)
Unbalanced				
Ten/10	.184 (.034)	.150 (.034)	.221 (.050)	.174 (.050)
$Ten^2/10^2$	-.107 (.024)	-.088 (.024)	-.214 (.044)	-.220 (.043)
$Ten^3/10^3$	.017 (.005)	.015 (.005)	.046 (.010)	.051 (.010)
Exp	.037 (.002)	.034 (.002)	.028 (.002)	.033 (.002)
Exp^2	-6.277e-4 (3.72e-5)	-5.981e-4 (3.75e-5)	-5.579e-4 (4.53e-5)	-6.404e-4 (6.55e-5)
Adj. R^2	.417	.414	.360	.370
Sample	7517	7517	5267	5267
T5	.067 (.012)	.055 (.012)	.063 (.016)	.038 (.016)
T10	.094 (.016)	.077 (.016)	.054 (.020)	.004 (.020)
T15	.093 (.016)	.076 (.017)	.007 (.021)	-.064 (.021)
T20	.077 (.016)	.065 (.017)	-.042 (.023)	-.128 (.023)
Balanced				
Ten/10	.161 (.053)	.144 (.054)	.144 (.080)	.120 (.079)
$Ten^2/10^2$	-.129 (.037)	-.117 (.037)	-.185 (.065)	-.182 (.063)
$Ten^3/10^3$	.027 (.007)	.025 (.007)	.042 (.014)	.041 (.014)
Exp	.035 (.003)	.031 (.003)	.018 (.003)	.025 (.004)
Exp^2	-5.837e-4 (5.95e-5)	-5.238e-4 (6.03e-5)	-2.895e-4 (6.94e-5)	-3.497e-4 (1.088e-4)
Adj. R^2	.437	.433	.340	.365
Sample	3167	3167	2231	2231

(*Table 2.7* continued)

T5	.052	.046	.031	.020
	(.019)	(.019)	(.027)	(.026)
T10	.059	.052	.001	-.021
	(.026)	(.026)	(.034)	(.033)
T15	.043	.037	-.057	-.091
	(.026)	(.027)	(.034)	(.033)
T20	.024	.019	-.113	-.160
	(.026)	(.026)	(.034)	(.033)

Notes: The estimated models include age left education, a cubic in tenure, a quadratic in experience, dummies for skills and a time trend. The actual labour market experience refers to only full-time employment. Standard errors presented in brackets.

Table 2.8

AS (1987) IV Method: Basic Estimates				
	Male		Female	
	1st Method	2nd Method	1st Method	2nd Method
$Ten/10$	.005	.009	.034	.038
	(.220)	(.318)	(.098)	(.099)
$Ten^2/10^2$	.050	.044	-.079	-.089
	(.281)	(.413)	(-.113)	(-.115)
$Ten^3/10^3$	-.011	-.008	.022	.024
	(.077)	(.115)	(.027)	(.027)
Exp	.037	.038	.015	.015
	(.007)	(.010)	(.002)	(.002)
Exp^2	-6.82e-4	-6.560e-4	-2.935e-4	-2.911e-4
	(1.749e-4)	(2.627e-4)	(4.11e-5)	(4.14e-5)
Adj. R^2	.407	.406	.336	.335
Sample	7642	7642	8849	8849
Hausman Test (P-value)	.143	.130	.000	.000
T5	.014	.014	-4.07e-5	-4.22e-5
	(.051)	(.071)	(.027)	(.027)
T10	.045	.045	-.023	-.026
	(.036)	(.037)	(.034)	(.034)
T15	.085	.085	-.053	-.060
	(.068)	(.083)	(.056)	(.056)
T20	.127	.129	-.072	-.084
	(.104)	(.124)	(.087)	(.088)

Notes: The estimated basic model includes age left education, a cubic in employer-tenure, a quadratic in potential labour market experience, dummies for individual's skills and a time trend. Standard errors presented in brackets.

Table 2.9

AS (1987) IV Method: Basic Estimates				
	Male		Female	
	1st Method	2nd Method	1st Method	2nd Method
Ten	.037	.033	-.033	-.036
	(.057)	(.058)	(.052)	(.052)
$Ten^2/10^2$	.011	.014	.004	.002
	(.030)	(.32)	(.027)	(.028)
Exp	.383	.038	.015	.015
	(.002)	(.002)	(.002)	(.002)
Exp^2	-6.05e-4	-6.370e-4	-2.79e-4	-2.61e-4
	(4.87e-5)	(5.00e-5)	(3.95e-5)	(3.98e-5)
Adj. R^2	.407	.406	.335	.335
Sample	7642	7642	8849	8849
Hausman Test (P-value)	.553	.534	.003	.002
T5	.021	.020	-.016	-.017
	(.023)	(.023)	(.021)	(.021)
T10	.048	.047	-.030	-.033
	(.037)	(.036)	(.035)	(.035)
T15	.081	.081	-.042	-.048
	(.049)	(.048)	(.049)	(.049)
T20	.119	.123	-.052	-.062
	(.071)	(.072)	(.072)	(.073)

Notes: The estimated basic model includes age left education, a cubic in employer-tenure, a quadratic in potential labour market experience, dummies for individual's skills and a time trend. Standard errors presented in brackets.

Table 2.10

AS (1987) IV Method: Alternative Wage Treatment Over Time					
	T5	T10	T15	T20	Hausman
Male full-time employees					
Unbalanced					
Time Trend	.014 (.071)	.045 (.037)	.085 (.083)	.129 (.124)	.130
Wave Dummies	.012 (.073)	.041 (.037)	.082 (.087)	.126 (.129)	.115
Real Wage (R.P.I.)	.012 (.072)	.068 (.039)	.142 (.079)	.211 (.120)	.148
Real Wage (R.P.I.) plus Time Trend	.015 (.071)	.042 (.037)	.079 (.083)	.121 (.124)	.118
Real Wage (A.E.I.)	.017 (.072)	-.012 (.039)	-.050 (.079)	-.061 (.121)	.003
Real Wage (A.E.I.) plus Time Trend	.012 (.071)	.041 (.037)	.081 (.083)	.125 (.124)	.111
Balanced					
Time Trend	-.265 (.969)	-.082 (.458)	.245 (.555)	.411 (1.017)	.714
Wave Dummies	-.448 (1.940)	-.177 (.945)	.328 (1.033)	.585 (1.963)	.668
Real Wage (R.P.I.)	-.061 (.246)	-.014 (.171)	.066 (.057)	.106 (.111)	.746
Real Wage (R.P.I.) plus Time Trend	-.251 (.940)	-.075 (.445)	.237 (.539)	.395 (.987)	.619
Real Wage (A.E.I.)	.091 (.246)	.031 (.171)	-.080 (.057)	-.139 (.111)	.110
Real Wage (A.E.I.) plus Time Trend	-.270 (.978)	-.086 (.462)	.244 (.560)	.411 (1.026)	.710

Notes: The estimated basic model includes age left education, a cubic in employer-tenure, a quadratic in potential labour market experience, dummies for individual's skills and a time trend. P-value of the performed Hausman test is presented in the last column. Standard errors presented in brackets

Table 2.11

AS (1987) IV Method: Alternative Wage Treatment Over Time					
	T 5	T 10	T 15	T 20	Hausman
Female full-time employees					
Unbalanced					
Time Trend	-4.20e-5 (.027)	-.026 (.034)	-.060 (.056)	-.084 (.088)	.000
Wave Dummies	-7.61e-4 (.028)	-.027 (.034)	-.061 (.057)	-.084 (.089)	.000
Real Wage (R.P.I.)	.045 (.027)	.120 (.031)	.207 (.053)	.285 (.087)	.015
Real Wage (R.P.I.) plus Time Trend	-.001 (.027)	-.030 (.034)	-.067 (.056)	-.093 (.088)	.000
Real Wage (A.E.I.)	.014 (.027)	.023 (.031)	.032 (.053)	.045 (.086)	.000
Real Wage (A.E.I.) plus Time Trend	-.003 (.027)	-.032 (.034)	-.069 (.056)	-.095 (.088)	.000
Balanced					
Time Trend	.012 (.040)	-.068 (.050)	-.191 (.083)	-.311 (.131)	.007
Wave Dummies	.011 (.042)	-.070 (.050)	-.193 (.084)	-.314 (.134)	.006
Real Wage (R.P.I.)	.050 (.039)	.102 (.039)	.146 (.056)	.173 (.095)	.261
Real Wage (R.P.I.) plus Time Trend	.013 (.040)	-.068 (.050)	-.196 (.083)	-.320 (.131)	.006
Real Wage (A.E.I.)	.031 (.039)	.024 (.039)	-.008 (.055)	-.047 (.095)	.254
Real Wage (A.E.I.) plus Time Trend	.011 (.040)	-.072 (.050)	-.199 (.083)	-.322 (.131)	.005

Notes: The estimated basic model includes age left education, a cubic in employer-tenure, a quadratic in potential labour market experience, dummies for individual's skills and a time trend. P-value of the performed Hausman test is presented in the last column. Standard errors presented in brackets

Table 2.12

AS (1987) IV Method: Alternative Wage Treatment Over Time					
	T 5	T 10	T 15	T 20	Hausman
Male full-time employees					
Unbalanced					
Time Trend	.020 (.023)	.047 (.036)	.081 (.048)	.123 (.072)	.534
Wave Dummies	.018 (.023)	.044 (.036)	.077 (.049)	.118 (.072)	.522
Real Wage (R.P.I.)	.034 (.022)	.077 (.036)	.128 (.050)	.187 (.076)	.310
Real Wage (R.P.I.) plus Time Trend	.018 (.023)	.044 (.036)	.077 (.048)	.117 (.072)	.531
Real Wage (A.E.I.)	-.016 (.022)	-.026 (.036)	-.029 (.050)	-.027 (.076)	.057
Real Wage (A.E.I.) plus Time Trend	.018 (.023)	.043 (.036)	.077 (.048)	.118 (.072)	.318
Balanced					
Time Trend	.035 (.030)	.068 (.053)	.099 (.074)	.129 (.103)	.343
Wave Dummies	.034 (.031)	.067 (.053)	.101 (.075)	.134 (.104)	.342
Real Wage (R.P.I.)	.025 (.026)	.048 (.041)	.069 (.054)	.087 (.076)	.401
Real Wage (R.P.I.) plus Time Trend	.035 (.030)	.068 (.053)	.098 (.074)	.126 (.103)	.349
Real Wage (A.E.I.)	-.027 (.026)	-.055 (.042)	-.083 (.055)	-.113 (.077)	.383
Real Wage (A.E.I.) plus Time Trend	.034 (.030)	.066 (.053)	.097 (.074)	.126 (.103)	.359

Notes: The estimated basic model includes age left education, a qudratic in employer-tenure, a quadratic in potential labour market experience, dummies for individual's skills and a time trend. P-value of the performed Hausman test is presented in the last column. Standard errors presented in brackets

Table 2.13

AS (1987) IV Method: Alternative Wage Treatment Over Time	T 5	T 10	T 15	T 20	Hausman
Female full-time employees					
Unbalanced					
Time Trend	-.017 (.021)	-.033 (.035)	-.048 (.049)	-.062 (.073)	.002
Wave Dummies	-.018 (.021)	-.034 (.035)	-.049 (.050)	-.062 (.074)	.002
Real Wage (R.P.I.)	.063 (.019)	.128 (.032)	.193 (.046)	.259 (.070)	.193
Real Wage (R.P.I.) plus Time Trend	-.019 (.021)	-.037 (.035)	-.054 (.049)	-.070 (.073)	.001
Real Wage (A.E.I.)	.010 (.019)	.022 (.032)	.035 (.045)	.050 (.070)	.092
Real Wage (A.E.I.) plus Time Trend	-.020 (.021)	-.039 (.035)	-.057 (.049)	-.073 (.073)	.001
Balanced					
Time Trend	-.049 (.031)	-.111 (.056)	-.189 (.082)	-.280 (.117)	.030
Wave Dummies	-.050 (.031)	-.113 (.056)	-.190 (.082)	-.280 (.118)	.032
Real Wage (R.P.I.)	.062 (.023)	.110 (.038)	.144 (.052)	.163 (.079)	.117
Real Wage (R.P.I.) plus Time Trend	-.050 (.031)	-.114 (.056)	-.193 (.082)	-.287 (.117)	.026
Real Wage (A.E.I.)	.013 (.023)	.012 (.037)	-.004 (.052)	-.033 (.079)	.732
Real Wage (A.E.I.) plus Time Trend	-.051 (.031)	-.116 (.056)	-.200 (.082)	-.290 (.117)	.024

Notes: The estimated basic model includes age left education, a quadratic in employer-tenure, a quadratic in potential labour market experience, dummies for individual's skills and a time trend. P-value of the performed Hausman test is presented in the last column. Standard errors presented in brackets

Table 2.14

AS (1987) IV Method: Actual and Potential Labour Market Experience	T5	T10	T15	T20	Hausman
Male full-time employees					
Unbalanced					
Potential labour market experience	.014 (.071)	.045 (.037)	.085 (.083)	.129 (.124)	.130
Actual labour market experience	.019 (.071)	.033 (.036)	.050 (.092)	.075 (.138)	.300
Balanced					
Potential labour market experience	-.265 (.969)	-.082 (.458)	.245 (.555)	.411 (1.017)	.714
Actual labour market experience	-.264 (.863)	-.080 (.397)	.247 (.524)	.409 (.933)	.727
Female full-time employees					
Unbalanced					
Potential labour market experience	-4.200e-5 (.027)	-.026 (.034)	-.060 (.056)	-.084 (.088)	.000
Actual labour market experience	-.021 (.027)	-.066 (.033)	-.116 (.055)	-.153 (.086)	.000
Balanced					
Potential labour market experience	.012 (.040)	-.068 (.050)	-.191 (.083)	-.311 (.131)	.007
Actual labour market experience	-.010 (.037)	-.084 (.048)	-.191 (.082)	-.298 (.128)	.013

Notes: The estimated basic model includes age left education, a cubic in employer-tenure, a quadratic in labour market experience, dummies for individual's skills and a time trend. Actual labour market experience refers to full-time employment only. P-value of the performed Hausman test is presented in the last column. Standard errors presented in brackets

Table 2.15

AS (1987) IV Method: Actual and Potential Labour Market Experience					
	T5	T10	T15	T20	Hausman
Male full-time employees					
Unbalanced					
Potential labour market experience	.020 (.023)	.047 (.036)	.081 (.048)	.123 (.072)	.534
Actual labour market experience	.014 (.023)	.032 (.037)	.054 (.049)	.082 (.072)	.741
Balanced					
Potential labour market experience	.035 (.030)	.068 (.053)	.099 (.074)	.129 (.103)	.343
Actual labour market experience	.034 (.031)	.066 (.054)	.096 (.075)	.124 (.104)	.360
Female full-time employees					
Unbalanced					
Potential labour market experience	-.017 (.021)	-.033 (.035)	-.048 (.049)	-.062 (.073)	.002
Actual labour market experience	-.038 (.021)	-.073 (.035)	-.105 (.049)	-.133 (.072)	.006
Balanced					
Potential labour market experience	-.049 (.031)	-.111 (.056)	-.189 (.082)	-.280 (.117)	.030
Actual labour market experience	-.050 (.030)	-.112 (.054)	-.188 (.080)	-.277 (.115)	.095

Notes: The estimated basic model includes age left education, a quadratic in employer-tenure, a quadratic in labour market experience, dummies for individual's skills and a time trend. Actual labour market experience refers to full-time employment only. P-value of the performed Hausman test is presented in the last column. Standard errors presented in brackets

Table 2.16

Male	AS (1987) IV Method: Alternative Control Vectors							
	Unbalanced				Balanced			
	Model 2	Model 3	Model 4	Model 5	Model 2	Model 3	Model 4	Model 5
Ten/10	.153	.089	.157	.186	.168	-.138	-.017	.001
	(.279))	(.285)	(.261)	(.259)	(1.043)	(1.105)	(.724)	(.734)
$Ten^2/10^2$	-.117	-.031	-.102	-.135	-.147	.231	.085	.071
	(.356))	(.368)	(.333)	(.331)	(1.282)	(1.367)	(.891)	(.899)
$Ten^3/10^3$	.033	.007	.026	.034	.039	-.065	-.023	-.022
	(.097))	(.101)	(.091)	(.090)	(.342)	(.368)	(.238)	(240)
Exp	.036	.037	.034	.034	.033	.024	.025	.024
	(.009)	(.009)	(.008)	(.008)	(.040)	(.043)	(.029)	(.029)
Exp^2	-6.715e-4	-6.402e-4	-5.955e-4	-5.968e-4	-6.309e-4	-3.827e-4	-4.369e-4	-4.244e-4
	(2.206e-4)	(2.300e-4)	(2.058e-4)	(2.049e-4)	(9.593e-4)	(.001)	(6.717e-4)	(6.679e-4)
T5	.051	.037	.056	.063	.052	-.020	.010	.016
	(.064)	(.064)	(.060)	(.059)	(.244)	(.258)	(.170)	(.173)
T10	.068	.065	.082	.084	.060	.028	.044	.050
	(.35)	(.035)	(.034)	(.034)	(.111)	(.115)	(.081)	(.084)
T15	.077	.087	.095	.088	.051	.093	.087	.088
	(.072)	(.078)	(.069)	(.069)	(.177)	(.189)	(.131)	(.130)
T20	.102	.109	.118	.100	.056	.128	.118	.112
	(.112)	(.119)	(.107)	(.108)	(.317)	(.328)	(.228)	(.231)
Hausman	.486	.237	.483	.673	.875	.948	.822	.924

Notes: **Model 2** is the Basic Model (age left education, a cubic in employer-tenure, a quadratic in potential labour market experience, dummies for individual's skills and a time trend) plus regional dummies, 1-digit industry dummies and establishment size dummies. **Model 3** is the Basic Model plus regional, occupational and qualification dummies. **Model 4** is Basic Model plus dummy variables for region, industry and occupation, establishment size and individual's qualifications. **Model 5** is Model 4 plus union coverage and union membership dummies. P-value of the performed Hausman test is presented in the last row. Standard errors presented in brackets

Table 2.17

AS (1987) IV Method: Alternative Control Vectors								
Female	Unbalanced				Balanced			
	Model 2	**Model 3**	**Model 4**	**Model 5**	**Model 2**	**Model 3**	**Model 4**	**Model 5**
Ten/10	-.034	.063	-.003	.064	-.044	.142	.017	.068
	(.088)	(.083)	(.078)	(.079)	(.120)	(.114)	(.106)	(.107)
$Ten^2/10^2$	.021	-.061	.026	-.042	-.040	-.168	-.027	-.072
	(.101)	(.096)	(.091)	(.092)	(.135)	(.132)	(.120)	(.122)
$Ten^3/10^3$	-.003	.017	-.004	.011	.007	.035	.002	.011
	(.024)	(.023)	(.021)	(.022)	(.031)	(.030)	(.027)	(.028)
Exp	.017	.013	.014	.014	.010	.006	.006	.006
	(.002)	(.001)	(.001)	(.001)	(.002)	(.002)	(.002)	(.002)
Exp^2	-3.138e-4	-2.668e-4	-2.844e-4	-2.699e-4	-1.308e-4	-8.470e-4	-7.970e-4	-6.490e-4
	(3.74e-5)	(3.55e-5)	(3.37e-5)	(3.37e-5)	(5.71e-5)	(5.48e-5)	(5.17e-5)	(5.18e-5)
T5	-.012	.018	.005	.023	-.031	.033	.002	.017
	(.024)	(.023)	(.022)	(.022)	(.034)	(.032)	(.030)	(.030)
T10	-.016	.019	.019	.033	-.077	.008	-.008	.006
	(.030)	(.029)	(.027)	(.028)	(.043)	(.042)	(.039)	(.039)
T15	-.015	.014	.040	.037	-.132	-.049	-.029	-.025
	(.050)	(.049)	(.046)	(.047)	(.069)	(.070)	(.065)	(.065)
T20	-.009	.016	.064	.045	-.192	-.113	-.059	-.067
	(.078)	(.076)	(.072)	(.073)	(.106)	(.109)	(.100)	(.101)
Hausman	.000	.000	.000	.001	.002	.048	.002	.016

Notes: **Model 2** is the Basic Model (age left education, a cubic in employer-tenure, a quadratic in potential labour market experience, dummies for individual's skills and a time trend) plus regional dummies, 1-digit industry dummies and establishment size dummies. **Model 3** is the Basic Model plus regional, occupational and qualification dummies. **Model 4** is Basic Model plus dummy variables for region, industry and occupation, establishment size and individual's qualifications. **Model 5** is Model 4 plus union coverage and union membership dummies. P-value of the performed Hausman test is presented in the last row. Standard errors presented in brackets

Table 2.18a

Topel (1991) Two-Step Method: Within-Job Wage Growth (1st step)				
	Male		Female	
	Method 1	Method 2	Method 1	Method 2
ΔTen	.124 (.020)	.091 (.017)	.056 (.019)	.037 (.016)
ΔTen^2	-.003 (.001)	-.002 (.001)	-.003 (.002)	-.003 (.002)
ΔTen^3	1.135e-4 (6.23e-5)	8.02e-5 (6.21e-5)	1.102e-4 (9.31e-5)	7.99e-5 (9.15e-5)
ΔTen^4	-1.42e-6 (8.95e-7)	-9.60e-7 (8.95e-7)	-1.17e-6 (1.59e-6)	-6.33e-7 (1.56e-6)
ΔExp^2	-.006 (.002)	-.003 (.002)	-.002 (.002)	-2.439e-4 (.001)
ΔExp^3	1.377e-4 (5.54e-5)	6.89e-5 (5.06e-5)	4.40e-5 (5.13e-5)	-2.20e-6 (4.70e-5)
ΔExp^4	-1.16e-6 (5.99e-7)	-4.87e-7 (5.57e-07)	-4.14e-7 (5.49e-7)	5.16e-8 (5.12e-7)

Notes: Dependent variable is the log real wage, constructed as nominal wage over the average earnings index (AEI). Standard errors presented in brackets.

Table 2.19a

Topel (1991) Two-Step Method: Derived Experience and Tenure Effects (2nd step)								
	Experience Effect	Within-Job Wage Growth	Tenure Effect	Adj. R^2	T5	T10	T15	T20
Method 1								
Male	.088	.124	.037	.583	.118	.154	.161	.170
Female	.033	.056	.023	.356	.041	-.018	-.121	-.230
Method 2								
Male	.063	.091	.027	.517	.085	.099	.081	.055
Female	.016	.037	.021	.209	.038	-.021	-.132	-.258

Notes: Estimated within-job wage growth from *Table 2.18a*. Tenure effect is constructed from within-job wage growth when experience effect is subtracted.

Table 2.18b

Topel (1991) Two-Step Method: Within-Job Wage Growth (1st step)				
	Male		Female	
	Method 1	Method 2	Method 1	Method 2
ΔTen	.126 (.020)	.092 (.017)	.070 (.019)	.050 (.016)
ΔTen^2	-.003 (.001)	-.003 (.001)	-.003 (.002)	-.003 (.002)
ΔTen^3	1.275e-4 (6.06e-5)	9.34e-5 (6.05e-5)	1.018e-4 (9.19e-5)	.7.03e-5 (9.03e-5)
ΔTen^4	-1.56e-6 (8.71e-7)	-1.10e-6 (8.71e-7)	-1.06e-6 (1.56e-6)	-5.00e-07 (1.54e-6)
ΔExp^2	-.005 (.002)	-.003 (.001)	-.002 (.002)	-2.451e-4 (.001)
ΔExp^3	1.194e-4 (5.41e-5)	4.76e-5 (4.94e-5)	4.12e-5 (5.04e-5)	-7.40e-6 (4.62e-5)
ΔExp^4	-1.02e-6 (5.85e-7)	-3.21e-7 (5.44e-7)	-3.34e-7 (5.41e-7)	1.57e-7 (5.04e-7)

Notes: Dependent variable is the log real wage, constructed as nominal wage over the retail price index (RPI).

Table 2.19b

Topel (1991) Two-Step Method: Derived Experience and Tenure Effects (2nd step)								
	Experience Effect	Within-Job Wage Growth	Tenure Effect	Adj. R^2	T5	T10	T15	T20
Method 1								
Male	.079	.126	.047	.569	.164	.237	.280	.330
Female	.036	.070	.034	.387	.096	.088	.029	-.043
Method 2								
Male	.054	.092	.038	.481	.130	.181	.200	.214
Female	.019	.050	.032	.225	.092	.084	.018	-.072

Notes: Estimated within-job wage growth from ***Table 2.18b***. Tenure effect is constructed from within-job wage growth when experience effect is subtracted.

Table 2.20

Topel (1991) Two-Step Method: Wage Treatment Over Time					
	T 5	T 10	T 15	T 20	Adj. R^2
Male full-time employees					
Unbalanced					
Time Trend	.271	.469	.634	.792	.504
Wave Dummies	.271	.469	.634	.792	.504
Real Wage (R.P.I.)	.130	.181	.200	.214	.481
Real Wage (R.P.I.) plus Time Trend	.131	.184	.204	.220	.487
Real Wage (A.E.I.)	.086	.099	.178	.362	.517
Real Wage (A.E.I.) plus Time Trend	.088	.121	.182	.367	.520
Balanced					
Time Trend	.317	.540	.732	.930	.578
Wave Dummies	.317	.540	.732	.930	.577
Real Wage (R.P.I.)	.185	.261	.302	.354	.540
Real Wage (R.P.I.) plus Time Trend	.188	.266	.309	.363	.562
Real Wage (A.E.I.)	.149	.208	.234	.265	.567
Real Wage (A.E.I.) plus Time Trend	.152	.213	.242	.275	.586

Notes: The returns to tenure are estimated in an equation that includes age left education, 4th order polynomials in employer tenure and potential experience and skill dummies.

Table 2.21

Topel (1991) Two-Step Method: Wage Treatment Over Time					
	T 5	T 10	T 15	T 20	Adj. R^2
Female full-time employees					
Unbalanced					
Time Trend	.237	.380	.461	.511	.241
Wave Dummies	.237	.380	.461	.511	.240
Real Wage (R.P.I.)	.092	.084	.018	-.072	.225
Real Wage (R.P.I.) plus Time Trend	.095	.090	.026	-.062	.240
Real Wage (A.E.I.)	.038	-.021	-.132	-.258	.209
Real Wage (A.E.I.) plus Time Trend	.040	-.018	-.127	-.251	.215
Balanced					
Time Trend	.200	.345	.436	.489	.251
Wave Dummies	.200	.345	.436	.489	.250
Real Wage (R.P.I.)	.078	.152	.303	.618	.207
Real Wage (R.P.I.) plus Time Trend	.079	.154	.305	.620	.210
Real Wage (A.E.I.)	.010	-.043	-.134	-.236	.212
Real Wage (A.E.I.) plus Time Trend	.010	-.043	-.134	-.236	.211

Notes: The returns to tenure are estimated in an equation that includes age left education, 4th order polynomials in employer tenure and potential experience and skill dummies.

Table 2.22a

Topel (1991) Two-Step Method: Potential and Actual Labour Market Experience	T5	T10	T15	T20	Adj. R^2
Male full-time employees					
Unbalanced					
Potential labour market experience	.085	.099	.081	.055	.517
Actual labour market experience	.080	.098	.085	.060	.546
Balanced					
Potential labour market experience	.149	.208	.234	.265	.567
Actual labour market experience	.149	.214	.248	.282	.580
Female full-time employees					
Unbalanced					
Potential labour market experience	.038	-.021	-.132	-.258	.209
Actual labour market experience	.024	-.043	-.163	-.307	.300
Balanced					
Potential labour market experience	.010	-.043	-.134	-.237	.212
Actual labour market experience	-.014	-.092	-.211	-.346	.218

Notes: Estimated equation includes age left education, 4th order polynomials in employer tenure and potential experience and skill dummies. Dependent variable is the log real wage based on the AEI. Actual labour market experience refers to full-time and part-time employment.

Table 2.22b

Topel (1991) Two-Step Method: Potential and Actual Labour Market Experience					
	T5	T10	T15	T20	Adj. R^2
Male full-time employees					
Unbalanced					
Potential labour market experience	.130	.181	.200	.214	.481
Actual labour market experience	.128	.185	.210	.228	.515
Balanced					
Potential labour market experience	.185	.261	.302	.354	.540
Actual labour market experience	.185	.265	.311	.367	.555
Female full-time employees					
Unbalanced					
Potential labour market experience	.092	.084	.018	-.072	.225
Actual labour market experience	.079	.065	-.009	-.116	.302
Balanced					
Potential labour market experience	.067	.058	-.030	-.204	.207
Actual labour market experience	.045	.021	-.058	-.174	.218

Notes: Estimated equation includes age left education, 4th order polynomials in employer tenure and potential experience and skill dummies. Dependent variable is the log real wage based on the RPI. Actual labour market experience refers to full-time and part-time employment.

Table 2.23

Topel (1991) Two-Step Method: Alternative Control Vectors					
	T 5	T 10	T 15	T 20	Adj. R^2
Male full-time employees					
Unbalanced					
Model 1	.085	.099	.081	.055	.517
Model 2	.116	.162	.175	.179	.607
Model 3	.127	.183	.206	.221	.585
Model 4	.131	.192	.219	.239	.624
Model 5	.130	.189	.215	.234	.631
Balanced					
Model 1	.149	.208	.234	.265	.567
Model 2	.191	.292	.361	.434	.643
Model 3	.211	.331	.420	.512	.646
Model 4	.215	.340	.432	.529	.672
Model 5	.212	.333	.422	.515	.682

Notes: The dependent variable is log real wage, constructed as nominal wage divided by the AEI. **Model 1** includes: age left education, 4^{th} order polynomials in both employer tenure and potential labour market experience and dummies for individual's skills. **Model 2** is Model 1 plus regional dummies, 1-digit industry dummies and establishment size dummies. **Model 3** is the Model 1 plus regional, occupational and qualification dummies. **Model 4** is Model 1 plus dummy variables for region, industry and occupation, establishment size and individual's qualifications. **Model 5** is Model 4 plus union coverage and union membership dummies.

Table 2.24

Topel (1991) Two-Step Method: Alternative Control Vectors					
	T 5	T 10	T 15	T 20	Adj. R^2
Female full-time employees					
Unbalanced					
Model 1	.038	-.021	-.132	-.258	.209
Model 2	.049	6.710e-4	-.099	-.215	.434
Model 3	.059	.021	-.069	-.175	.473
Model 4	.058	.019	-.072	-.179	.520
Model 5	.059	.020	-.071	-.176	.528
Balanced					
Model 1	.010	-.043	-.134	-.238	.212
Model 2	.012	-.039	-.129	-.230	.477
Model 3	.029	-.005	-.078	-.163	.514
Model 4	.026	-.012	-.088	-.176	.561
Model 5	.025	-.014	-.090	-.179	.566

Notes: The dependent variable is log real wage, constructed as nominal wage divided by the AEI. **Model 1** includes: age left education, 4th order polynomials in both employer tenure and potential labour market experience and dummies for individual's skills. **Model 2** is Model 1 plus regional dummies, 1-digit industry dummies and establishment size dummies. **Model 3** is the Model 1 plus regional, occupational and qualification dummies. **Model 4** is Model 1 plus dummy variables for region, industry and occupation, establishment size and individual's qualifications. **Model 5** is Model 4 plus union coverage and union membership dummies.

Table 2.25

Topel (1991) Two-Step Method: Alternative Control Vectors					
	T 5	T 10	T 15	T 20	Adj. R^2
Male full-time employees					
Unbalanced					
Model 1	.130	.181	.200	.214	.481
Model 2	.160	.243	.292	.337	.591
Model 3	.168	.258	.315	.368	.564
Model 4	.172	.266	.327	.385	.608
Model 5	.171	.264	.324	.380	.615
Balanced					
Model 1	.185	.261	.302	.354	.540
Model 2	.226	.343	.424	.516	.633
Model 3	.241	.373	.469	.577	.631
Model 4	.245	.381	.481	.592	.661
Model 5	.242	.375	.472	.580	.671

Notes: The dependent variable is log real wage, constructed as nominal wage divided by the RPI. **Model 1** includes: age left education, 4^{th} order polynomials in both employer tenure and potential labour market experience and dummies for individual's skills. **Model 2** is Model 1 plus regional dummies, 1-digit industry dummies and establishment size dummies. **Model 3** is the Model 1 plus regional, occupational and qualification dummies. **Model 4** is Model 1 plus dummy variables for region, industry and occupation, establishment size and individual's qualifications. **Model 5** is Model 4 plus union coverage and union membership dummies.

Table 2.26

Topel (1991) Two-Step Method: Alternative Control Vectors					
	T 5	T 10	T 15	T 20	Adj. R^2
Female full-time employees					
Unbalanced					
Model 1	.092	.084	.018	-.072	.225
Model 2	.103	.106	.051	-.029	.444
Model 3	.113	.126	.081	.011	.481
Model 4	.112	.124	.078	.007	.527
Model 5	.113	.125	.080	.010	.536
Balanced					
Model 1	.078	.152	.303	.618	.207
Model 2	.081	.157	.309	.626	.473
Model 3	.097	.190	.360	.694	.508
Model 4	.094	.184	.351	.681	.556
Model 5	.093	.182	.348	.678	.563

Notes: The dependent variable is log real wage, constructed as nominal wage divided by the RPI. **Model 1** includes: age left education, 4th order polynomials in both employer tenure and potential labour market experience and dummies for individual's skills. **Model 2** is Model 1 plus regional dummies, 1-digit industry dummies and establishment size dummies. **Model 3** is the Model 1 plus regional, occupational and qualification dummies. **Model 4** is Model 1 plus dummy variables for region, industry and occupation, establishment size and individual's qualifications. **Model 5** is Model 4 plus union coverage and union membership dummies.

Table 2.27

Topel (1991) Two-Step Method: Alternative Control Vectors					
	T 5	T 10	T 15	T 20	Adj. R^2
Male full-time employees					
Unbalanced					
Model 1	.059	.050	-.005	-.087	.303
Model 2	.088	.109	.083	.030	.501
Model 3	.091	.115	.092	.041	.455
Model 4	.094	.121	.101	.054	.522
Model 5	.093	.119	.098	.050	.528
Balanced					
Model 1	.069	.057	-.009	-.100	.300
Model 2	.106	.130	.101	.047	.529
Model 3	.109	.137	.111	.060	.500
Model 4	.112	.143	.120	.072	.553
Model 5	.111	.140	.115	.066	.559

Notes: The dependent variable is log real wage, constructed as nominal wage divided by the AEI. **Model 1** includes: age left education, a cubic in employer tenure, a quadratic in potential labour market experience and dummies for individual's skills. **Model 2** is Model 1 plus regional dummies, 1-digit industry dummies and establishment size dummies. **Model 3** is the Model 1 plus regional, occupational and qualification dummies. **Model 4** is Model 1 plus dummy variables for region, industry and occupation, establishment size and individual's qualifications. **Model 5** is Model 4 plus union coverage and union membership dummies.

Table 2.28

Topel (1991) Two-Step Method: Alternative Control Vectors					
	T 5	T 10	T 15	T 20	Adj. R^2
Female full-time employees					
Unbalanced					
Model 1	.037	-.016	-.128	-.265	.201
Model 2	.048	.005	-.096	-.222	.429
Model 3	.058	.025	-.066	-.182	.469
Model 4	.057	.023	-.069	-.187	.516
Model 5	.058	.024	-.068	-.184	.524
Balanced					
Model 1	.012	-.037	-.123	-.220	.205
Model 2	.014	-.032	-.116	-.211	.470
Model 3	.032	.002	-.064	-.141	.505
Model 4	.029	-.004	-.073	-.153	.552
Model 5	.028	-.006	-.076	-.158	.560

Notes: The dependent variable is log real wage, constructed as nominal wage divided by the AEI. **Model 1** includes: age left education, a cubic in employer tenure, a quadratic in potential labour market experience and dummies for individual's skills. **Model 2** is Model 1 plus regional dummies, 1-digit industry dummies and establishment size dummies. **Model 3** is the Model 1 plus regional, occupational and qualification dummies. **Model 4** is Model 1 plus dummy variables for region, industry and occupation, establishment size and individual's qualifications. **Model 5** is Model 4 plus union coverage and union membership dummies.

Table 2.29

Topel (1991) Two-Step Method: Alternative Control Vectors					
	T 5	T 10	T 15	T 20	Adj. R^2
Male full-time employees					
Unbalanced					
Model 1	.108	.149	.144	.112	.308
Model 2	.138	.208	.232	.230	.505
Model 3	.140	.213	.239	.239	.461
Model 4	.143	.219	.248	.251	.527
Model 5	.142	.217	.246	.248	.533
Balanced					
Model 1	.116	.148	.127	.085	.322
Model 2	.153	.222	.238	.232	.539
Model 3	.157	.230	.249	.247	.512
Model 4	.160	.236	.258	.259	.563
Model 5	.158	.232	.253	.253	.570

Notes: The dependent variable is log real wage, constructed as nominal wage divided by the RPI. **Model 1** includes: age left education, a cubic in employer tenure, a quadratic in potential labour market experience and dummies for individual's skills. **Model 2** is Model 1 plus regional dummies, 1-digit industry dummies and establishment size dummies. **Model 3** is the Model 1 plus regional, occupational and qualification dummies. **Model 4** is Model 1 plus dummy variables for region, industry and occupation, establishment size and individual's qualifications. **Model 5** is Model 4 plus union coverage and union membership dummies.

Table 2.30

Topel (1991) Two-Step Method: Alternative Control Vectors					
	T 5	T 10	T 15	T 20	Adj. R^2
Female full-time employees					
Unbalanced					
Model 1	.083	.007	-.259	-.748	.201
Model 2	.094	.029	-.227	-.705	.430
Model 3	.103	.048	-.198	-.667	.471
Model 4	.102	.046	-.201	-.671	.518
Model 5	.103	.047	-.200	-.669	.527
Balanced					
Model 1	.071	.070	.019	-.056	.207
Model 2	.074	.074	.026	-.047	.471
Model 3	.091	.109	.078	.022	.506
Model 4	.088	.103	.069	.010	.553
Model 5	.087	.100	.065	.005	.563

Notes: The dependent variable is log real wage, constructed as nominal wage divided by the RPI. **Model 1** includes: age left education, a cubic in employer tenure, a quadratic in potential labour market experience and dummies for individual's skills. **Model 2** is Model 1 plus regional dummies, 1-digit industry dummies and establishment size dummies. **Model 3** is the Model 1 plus regional, occupational and qualification dummies. **Model 4** is Model 1 plus dummy variables for region, industry and occupation, establishment size and individual's qualifications. **Model 5** is Model 4 plus union coverage and union membership dummies.

Table 2.31

Panel Estimates on Tenure Effect: Potential and Actual Experience				
	Male		Female	
	Potential	Actual	Potential	Actual
Random Effects				
Ten/10	.151	.134	.259	.209
	(.032)	(.032)	(.040)	(.040)
$Ten^2/(10)^2$	-.113	-.103	-.222	-.221
	(.023)	(.023)	(.033)	(.033)
$Ten^3/(10)^3$	.021	.019	.044	.046
	(.005)	(.005)	(.008)	(.008)
Exp	.037	.034	.019	.029
	(.002)	(.002)	(.002)	(.003)
Exp^2	-5.818e-4	-5.587e-4	-3.452e-4	-5.172e-4
	(4.7e-5)	(4.78e-5)	(5.08e-5)	(7.32e-5)
Adj. R^2	.368	.362	.304	.322
Hausman Test (1978) x^2 (11)	384.08	431.10	226.43	159.67
T5	.050	.044	.079	.055
	(.011)	(.012)	(.014)	(.014)
T10	.059	.050	.081	.034
	(.017)	(.017)	(.021)	(.021)
T15	.042	.034	.037	-.028
	(.020)	(.021)	(.027)	(.027)
T20	.015	.008	-.019	-.096
	(.024)	(.024)	(.034)	(.034)
Fixed Effects				
Ten/10	.198	.187	.313	.321
	(.039)	(.040)	(.048)	(.048)
$Ten^2/(10)^2$	-.150	-.142	-.238	-.247
	(.026)	(.026)	(.035)	(.035)
$Ten^3/(10)^3$	.028	.027	.045	.047
	(.006)	(.006)	(.008)	(.008)
Exp	-	-	-	-
Exp^2	-4.182e-4	-4.410e-4	-2.213e-4	-2.714e-4
	(6.21e-5)	(6.31e-5)	(6.10e-5)	(8.38e-5)
Adj. R^2	.218	.218	.285	.285
T5	.065	-	.103	-
	(.015)		(.019)	
T10	.077	-	.120	-
	(.025)		(.032)	
T15	.056	-	.085	-
	(.032)		(.043)	
T20	.024	-	.032	-
	(.039)		(.055)	

Notes: Estimated model includes age left education, cubic in tenure, quadratic in labour market experience, skill dummies and a time trend. Actual labour market experience refers to full-time employment only. Sample includes full-time male and female employees from the unbalanced panel sample. Standard errors presented in brackets. R^2 is defined as the within for the fixed-effects model and overall for the random-effects model.

Table 2.32

Panel Estimates on Tenure Effect: Potential and Actual Experience				
	Male		Female	
	Potential	Actual	Potential	Actual
Random Effects				
Ten/10	.136 (.048)	.125 (.048)	.203 (.058)	.183 (.057)
$Ten^2/(10)^2$	-.120 (.035)	-.113 (.035)	-.165 (.044)	-.163 (.044)
$Ten^3/(10)^3$	.025 (.007)	.024 (.007)	.031 (.010)	.032 (.010)
Exp	.031 (.004)	.030 (.004)	.014 (.004)	.025 (.004)
Exp^2	-4.513e-4 (7.24e-5)	-4.628e-4 (7.28e-5)	-1.853e-4 (7.29e-5)	-3.340e-4 (1.046e-4)
Adj. R^2	.385	.378	.276	.306
Hausman Test (1978) x^2 (12)	168.11	172.76	83.69	62.51
T5	.041 (.018)	.037 (.018)	.064 (.021)	.055 (.021)
T10	.041 (.026)	.036 (.027)	.069 (.031)	.051 (.031)
T15	.018 (.032)	.013 (.032)	.038 (.038)	.014 (.038)
T20	-.008 (.037)	-.012 (.037)	-.007 (.046)	-.034 (.045)
Fixed Effects				
Ten/10	.183 (.055)	.172 (.055)	.253 (.062)	.261 (.062)
$Ten^2/(10)^2$	-.134 (.038)	-.127 (.038)	-.172 (.045)	-.181 (.045)
$Ten^3/(10)^3$	.026 (.008)	.025 (.008)	.031 (.010)	.033 (.010)
Exp	-	-	-	-
Exp^2	-3.334e-4 (8.22e-5)	-3.761e-4 (8.29e-5)	-1.618e-4 (7.94e-5)	-1.920e-4 (1.058e-4)
Adj. R^2	.233	.235	.297	.296
T5	.061 (.021)	-	.087 (.023)	-
T10	.075 (.034)	-	.112 (.037)	-
T15	.062 (.045)	-	.097 (.048)	-
T20	.041 (.055)	-	.066 (.059)	-

Notes: Estimated model includes age left education, cubic in tenure, quadratic in labour market experience, skill dummies and a time trend. Actual labour market experience refers to full-time employment only. Sample includes full-time male and female employees from the balanced panel sample. Standard errors presented in brackets. R^2 is defined as the within for the fixed-effects model and overall for the random-effects model.

Table 2.33

Panel Estimates on Tenure Effect: Wage Treatment Over Time										
	Random Effects					Fixed Effects				
Unbalanced Sample	T 5	T 10	T 15	T 20	Adj. R^2	T 5	T 10	T 15	T 20	Adj. R^2
Male full-time employees										
Time Trend	.050 (.011)	.059 (.017)	.042 (.020)	.015 (.024)	.368	.065 (.015)	.077 (.025)	.056 (.032)	.024 (.039)	.218
Wave Dummies	.049 (.011)	.058 (.017)	.041 (.020)	.015 (.024)	.368	.065 (.015)	.078 (.025)	.059 (.032)	.029 (.039)	.221
Real Wage (R.P.I.)	.060 (.010)	.075 (.015)	.062 (.017)	.037 (.021)	.346	.144 (.012)	.214 (.019)	.234 (.025)	.227 (.032)	.045
Real Wage (R.P.I.) plus Time Trend	.049 (.011)	.057 (.017)	.040 (.020)	.013 (.024)	.347	.064 (.015)	.075 (.025)	.054 (.032)	.022 (.039)	.057
Real Wage (A.E.I.)	.028 (.010)	.022 (.015)	-.003 (.017)	-.033 (.021)	.343	.118 (.012)	.171 (.019)	.179 (.025)	.165 (.032)	.020
Real Wage (A.E.I.) plus Time Trend	.049 (.011)	.057 (.017)	.040 (.020)	.014 (.024)	.344	.064 (.015)	.076 (.025)	.056 (.032)	.024 (.039)	.026
Female full-time employees										
Time Trend	.079 (.014)	.081 (.021)	.037 (.027)	-.019 (.034)	.304	.103 (.019)	.120 (.032)	.085 (.043)	.032 (.055)	.285
Wave Dummies	.080 (.014)	.081 (.021)	.036 (.027)	-.020 (.034)	.304	.103 (.019)	.120 (.032)	.085 (.043)	.031 (.055)	.286
Real Wage (R.P.I.)	.128 (.011)	.163 (.016)	.141 (.021)	.097 (.028)	.258	.174 (.013)	.243 (.021)	.246 (.030)	.219 (.041)	.081
Real Wage (R.P.I.) plus Time Trend	.078 (.014)	.079 (.021)	.034 (.027)	-.023 (.034)	.273	.102 (.019)	.117 (.032)	.081 (.043)	.027 (.055)	.087
Real Wage (A.E.I.)	.088 (.011)	.096 (.016)	.057 (.021)	.003 (.027)	.265	.140 (.013)	.185 (.021)	.170 (.030)	.130 (.041)	.040
Real Wage (A.E.I.) plus Time Trend	.077 (.014)	.078 (.021)	.033 (.027)	-.023 (.034)	.267	.100 (.019)	.115 (.032)	.080 (.043)	.025 (.055)	.043

Notes: Basic model includes age left education, cubic in tenure, quadratic in labour market experience and skill dummies. Standard errors presented in brackets. R^2 is defined as the within for the fixed-effects model and overall for the random-effects model.

Table 2.34

Panel Estimates on Tenure Effect: Wage Treatment Over Time										
	Random Effects					Fixed Effects				
Balanced Sample	T 5	T 10	T 15	T 20	Adj. R^2	T 5	T 10	T 15	T 20	Adj. R^2
Male full-time employees										
Time Trend	.041 (.018)	.041 (.026)	.018 (.032)	-.008 (.037)	.385	.061 (.021)	.075 (.034)	.062 (.045)	.041 (.055)	.233
Wave Dummies	.040 (.018)	.040 (.026)	.019 (.032)	-.005 (.037)	.386	.061 (.021)	.077 (.034)	.067 (.045)	.049 (.055)	.239
Real Wage (R.P.I.)	.048 (.016)	.052 (.023)	.032 (.026)	.007 (.031)	.361	.118 (.018)	.181 (.018)	.205 (.035)	.210 (.043)	.038
Real Wage (R.P.I.) plus Time Trend	.042 (.018)	.042 (.026)	.018 (.032)	-.009 (.037)	.363	.062 (.021)	.076 (.034)	.061 (.045)	.039 (.055)	.047
Real Wage (A.E.I.)	.015 (.016)	-.004 (.023)	-.040 (.026)	-.075 (.031)	.360	.094 (.018)	.137 (.027)	.147 (.035)	.142 (.043)	.016
Real Wage (A.E.I.) plus Time Trend	.040 (.018)	.040 (.026)	.017 (.032)	-.009 (.037)	.360	.060 (.021)	.074 (.034)	.061 (.045)	.040 (.055)	.019
Female full-time employees										
Time Trend	.064 (.021)	.069 (.031)	.038 (.038)	-.007 (.046)	.276	.087 (.023)	.112 (.037)	.097 (.048)	.066 (.059)	.297
Wave Dummies	.064 (.021)	.069 (.031)	.039 (.038)	-.005 (.046)	.276	.088 (.023)	.113 (.037)	.099 (.048)	.069 (.059)	.299
Real Wage (R.P.I.)	.092 (.017)	.114 (.025)	.093 (.030)	.054 (.037)	.240	.134 (.018)	.190 (.027)	.195 (.036)	.176 (.047)	.064
Real Wage (R.P.I.) plus Time Trend	.065 (.021)	.069 (.031)	.037 (.038)	-.009 (.046)	.250	.088 (.023)	.112 (.037)	.096 (.048)	.062 (.059)	.069
Real Wage (A.E.I.)	.055 (.017)	.053 (.025)	.018 (.030)	-.030 (.037)	.249	.104 (.018)	.139 (.027)	.131 (.036)	.103 (.047)	.027
Real Wage (A.E.I.) plus Time Trend	.063 (.021)	.067 (.031)	.035 (.038)	-.010 (.046)	.248	.086 (.023)	.110 (.037)	.093 (.048)	.060 (.059)	.027

Notes: Basic model includes age left education, cubic in tenure, quadratic in labour market experience and skill dummies. Standard errors presented in brackets. R^2 is defined as the within for the fixed-effects model and overall for the random-effects model.

Table 2.35

Panel Estimates on Tenure Effect: Alternative Control Vectors (Male Employees)				
Unbalanced	Model 2	Model 3	Model 4	Model 5
Random Effects				
Ten/10	.148	.178	.175	.171
	(.031)	(.031)	(.031)	(.031)
$Ten^2/10^2$	-.110	-.120	-.120	-.117
	(.023)	(.023)	(.023)	(.023)
$Ten^3/10^3$	.020	.022	.022	.021
	(.005)	(.005)	(.005)	(.005)
Exp	.036	.037	.035	.035
	(.002)	(.002)	(.002)	(.002)
Exp^2	-5.780e-4	-5.655e-4	-5.504e-4	-5.507e-4
	(4.55e-5)	(4.61e-5)	(4.48e-5)	(4.48e-5)
Adj. R^2	.447	.433	.481	.481
T5	.049	.062	.060	.059
	(.011)	(.011)	(.011)	(.011)
T10	.059	.079	.077	.076
	(.016)	(.017)	(.016)	(.016)
T15	.044	.069	.067	.067
	(.020)	(.020)	(.019)	(.019)
T20	.020	.048	.046	.047
	(.023)	(.023)	(.022)	(.022)
Fixed Effects				
Ten/10	.200	.190	.192	.184
	(.040)	(.040)	(.040)	(.040)
$Ten^2/10^2$	-.150	-.147	-.148	-.141
	(.026)	(.027)	(.027)	(.027)
$Ten^3/10^3$	.028	.028	.029	.027
	(.006)	(.006)	(.006)	(.006)
Exp	-	-	-	-
Exp^2	-4.069e-4	-4.029e-4	-4.037e-4	-3.993e-4
	(6.25e-5)	(6.30e-5)	(6.30e-5)	(6.30e-5)
Adj. R^2	.221	.222	.224	.226
T5	.066	.062	.063	.060
	(.015)	(.015)	(.015)	(.015)
T10	.078	.072	.073	.071
	(.025)	(.025)	(.025)	(.025)
T15	.058	.050	.052	.051
	(.032)	(.032)	(.032)	(.032)
T20	.027	.019	.021	.023
	(.039)	(.040)	(.040)	(.040)

Notes: Model 2 is the Basic Model (age left education, a cubic in employer-tenure, a quadratic in potential labour market experience, dummies for individual's skills and a time trend) plus regional dummies, 1-digit industry dummies and establishment size dummies. Model 3 is the Basic Model plus regional, occupational and qualification dummies. Model 4 is Basic Model plus dummy variables for region, industry and occupation, establishment size and individual's qualifications. Model 5 is Model 4 plus union coverage and union membership dummies. Standard errors presented in brackets. R^2 is defined as the within for the fixed-effects model and overall for the random-effects model.

Table 2.36

Panel Estimates on Tenure Effect: Alternative Control Vectors (Female Employees)				
Unbalanced	Model 2	Model 3	Model 4	Model 5
Random Effects				
Ten/10	.244 (.039)	.260 (.038)	.256 (.038)	.258 (.039)
$Ten^2/10^2$	-.206 (.033)	-.211 (.032)	-.205 (.032)	-.208 (.033)
$Ten^3/10^3$	.041 (.008)	.042 (.008)	.041 (.008)	.041 (.008)
Exp	.021 (.002)	.018 (.002)	.019 (.002)	.019 (.002)
Exp^2	-3.847e-4 (5.01e-5)	-3.637e-4 (4.91e-5)	-3.712e-4 (4.86e-5)	-3.752e-4 (4.86e-5)
Adj. R^2	.377	.460	.496	.498
T5	.076 (.014)	.082 (.013)	.082 (.013)	.082 (.013)
T10	.079 (.020)	.091 (.020)	.091 (.020)	.092 (.020)
T15	.039 (.026)	.057 (.025)	.060 (.025)	.059 (.025)
T20	-.011 (.032)	.012 (.031)	.018 (.031)	.016 (.030)
Fixed Effects				
Ten/10	.290 (.048)	.277 (.048)	.279 (.048)	.276 (.048)
$Ten^2/10^2$	-.217 (.035)	-.212 (.035)	-.212 (.035)	-.210 (.035)
$Ten^3/10^3$	.040 (.008)	.039 (.008)	.040 (.008)	.039 (.008)
Exp	-	-	-	-
Exp^2	-2.318e-4 (6.07e-5)	-2.116e-4 (6.12e-5)	-2.150e-4 (6.14e-5)	-2.158e-4 (6.14e-5)
Adj. R^2	.312	.316	.318	.318
T5	.096 (.019)	.091 (.019)	.091 (.019)	.091 (.019)
T10	.114 (.031)	.105 (.031)	.106 (.031)	.105 (.031)
T15	.083 (.043)	.072 (.042)	.073 (.043)	.074 (.043)
T20	.036 (.054)	.021 (.054)	.023 (.054)	.024 (.054)

Notes: Model 2 is the Basic Model (age left education, a cubic in employer-tenure, a quadratic in potential labour market experience, dummies for individual's skills and a time trend) plus regional dummies, 1-digit industry dummies and establishment size dummies. Model 3 is the Basic Model plus regional, occupational and qualification dummies. Model 4 is Basic Model plus dummy variables for region, industry and occupation, establishment size and individual's qualifications. Model 5 is Model 4 plus union coverage and union membership dummies. Standard errors presented in brackets. R^2 is defined as the within for the fixed-effects model and overall for the random-effects model.

Table 2.37

Panel Estimates on Tenure Effect: Alternative Control Vectors (Male Employees)				
Balanced	Model 2	Model 3	Model 4	Model 5
Random Effects				
Ten/10	.121 (.048)	.135 (.048)	.132 (.048)	.126 (.048)
$Ten^2/10^2$	-.105 (.034)	-.112 (.034)	-.110 (.034)	-.104 (.034)
$Ten^3/10^3$	.022 (.007)	.023 (.007)	.023 (.007)	.022 (.007)
Exp	.029 (.004)	.029 (.004)	.028 (.004)	.028 (.004)
Exp^2	-4.425e-4 (7.19e-5)	-4.329e-4 (7.25e-5)	-4.372e-4 (7.19e-5)	-4.359e-4 (7.18e-5)
Adj. R^2	.454	.456	.489	.487
T5	.037 (.017)	.042 (.018)	.042 (.017)	.040 (.017)
T10	.038 (.026)	.046 (.026)	.045 (.026)	.044 (.026)
T15	.019 (.031)	.028 (.032)	.028 (.031)	.028 (.031)
T20	-.003 (.036)	.006 (.037)	.007 (.036)	.009 (.036)
Fixed Effects				
Ten/10	.171 (.055)	.174 (.055)	.170 (.056)	.159 (.056)
$Ten^2/10^2$	-.127 (.038)	-.129 (.038)	-.127 (.038)	-.119 (.039)
$Ten^3/10^3$	.025 (.008)	.025 (.009)	.025 (.009)	.024 (.009)
Exp	-	-	-	-
Exp^2	-3.022e-4 (8.31e-5)	-2.995e-4 (8.39e-5)	-3.053e-4 (8.44e-5)	-2.958e-4 (8.44e-5)
Adj. R^2	.244	.243	.248	.251
T5	.057 (.021)	.058 (.021)	.056 (.021)	.053 (.021)
T10	.070 (.034)	.070 (.035)	.067 (.035)	.064 (.035)
T15	.056 (.045)	.057 (.045)	.053 (.045)	.052 (.045)
T20	.036 (.055)	.036 (.055)	.032 (.056)	.035 (.055)

Notes: Model 2 is the Basic Model (age left education, a cubic in employer-tenure, a quadratic in potential labour market experience, dummies for individual's skills and a time trend) plus regional dummies, 1-digit industry dummies and establishment size dummies. Model 3 is the Basic Model plus regional, occupational and qualification dummies. Model 4 is Basic Model plus dummy variables for region, industry and occupation, establishment size and individual's qualifications. Model 5 is Model 4 plus union coverage and union membership dummies. Standard errors presented in brackets. R^2 is defined as the within for the fixed-effects model and overall for the random-effects model.

Table 2.38

Panel Estimates on Tenure Effect: Alternative Control Vectors (Female Employees)				
Balanced	Model 2	Model 3	Model 4	Model 5
Random Effects				
Ten/10	.199 (.058)	.203 (.057)	.209 (.057)	.212 (.058)
$Ten^2/10^2$	-.162 (.045)	-.158 (.044)	-.159 (.045)	-.162 (.045)
$Ten^3/10^3$	.030 (.010)	.030 (.010)	.030 (.010)	.031 (.010)
Exp	.016 (.004)	.014 (.004)	.013 (.004)	.013 (.004)
Exp^2	-2.030e-4 (7.33e-5)	-2.113e-4 (7.20e-5)	-1.943e-4 (7.20e-5)	-1.961e-4 (7.20e-5)
Adj. R^2	.0395	.488	.510	.514
T5	.063 (.021)	.066 (.020)	.069 (.020)	.069 (.020)
T10	.067 (.031)	.075 (.030)	.081 (.030)	.081 (.030)
T15	.037 (.037)	.050 (.036)	.058 (.036)	.058 (.036)
T20	-.007 (.044)	.013 (.043)	.024 (.043)	.022 (.043)
Fixed Effects				
Ten/10	.268 (.063)	.238 (.063)	.259 (.064)	.260 (.064)
$Ten^2/10^2$	-.178 (.046)	-.163 (.046)	-.173 (.046)	-.173 (.046)
$Ten^3/10^3$	.032 (.010)	.029 (.010)	.031 (.011)	.031 (.011)
Exp	-	-	-	-
Exp^2	-1.787e-4 (8.10e-5)	-1.794e-4 (8.23e-5)	-1.740e-4 (8.25e-5)	-1.762e-4 (8.26e-5)
Adj. R^2	.308	.306	.312	.313
T5	.094 (.024)	.082 (.024)	.090 (.024)	.091 (.024)
T10	.123 (.037)	.104 (.037)	.117 (.038)	.118 (.038)
T15	.111 (.048)	.089 (.048)	.105 (.049)	.106 (.049)
T20	.084 (.060)	.057 (.059)	.076 (.060)	.078 (.060)

Notes: Model 2 is the Basic Model (age left education, a cubic in employer-tenure, a quadratic in potential labour market experience, dummies for individual's skills and a time trend) plus regional dummies, 1-digit industry dummies and establishment size dummies. Model 3 is the Basic Model plus regional, occupational and qualification dummies. Model 4 is Basic Model plus dummy variables for region, industry and occupation, establishment size and individual's qualifications. Model 5 is Model 4 plus union coverage and union membership dummies. Standard errors presented in brackets. R^2 is defined as the within for the fixed-effects model and overall for the random-effects model.

Table 2.39

Quantile (Median) Estimates on Tenure Effect					
	Model 1	Model 2	Model 3	Model 4	Model 5
Pooled					
Ten/10	.136 (.035)	.111 (.034)	.223 (.025)	.182 (.024)	.191 (.022)
$Ten^2/10^2$	-.093 (.026)	-.066 (.026)	-.130 (.019)	-.108 (.018)	-.121 (.016)
$Ten^3/10^3$	.018 (.005)	.012 (.005)	.023 (.004)	.019 (.003)	.022 (.003)
Exp	.038 (.002)	.033 (.002)	.030 (.001)	.028 (.001)	.028 (.001)
Exp^2	-6.847e-4 (3.60e-5)	-6.109e-4 (3.58e-5)	-5.350e-4 (2.63e-5)	-4.962e-4 (2.49e-5)	-4.964e-4 (2.33e-5)
Pseudo R^2	.232	.298	.306	.350	.352
T5	.047 (.012)	.040 (.012)	.082 (.009)	.066 (.008)	.068 (.008)
T10	.062 (.016)	.056 (.016)	.116 (.011)	.093 (.011)	.092 (.010)
T15	.058 (.016)	.057 (.016)	.120 (.012)	.094 (.011)	.088 (.011)
T20	.048 (.017)	.051 (.017)	.111 (.012)	.083 (.012)	.072 (.011)
Male					
Ten/10	.120 (.042)	.086 (.040)	.137 (.035)	.152 (.034)	.156 (.032)
$Ten^2/10^2$	-.070 (.030)	-.050 (.029)	-.074 (.025)	-.088 (.024)	-.095 (.023)
$Ten^3/10^3$	.012 (.006)	.009 (.005)	.013 (.005)	.015 (.005)	.017 (.004)
Exp	.039 (.002)	.036 (.002)	.037 (.002)	.033 (.002)	.032 (.002)
Exp^2	-6.667e-4 (4.55e-5)	-6.218e-4 (4.46e-5)	-6.148e-4 (3.88e-5)	-5.581e-4 (3.79e-5)	-5.449e-4 (3.56e-5)
Pseudo R^2	.269	.331	.317	.360	.362
T5	.044 (.015)	.031 (.014)	.052 (.012)	.056 (.012)	.056 (.011)
T10	.062 (.020)	.044 (.019)	.076 (.017)	.080 (.016)	.078 (.015)
T15	.061 (.020)	.046 (.020)	.083 (.017)	.082 (.017)	.078 (.016)
T20	.052 (.020)	.041 (.020)	.082 (.017)	.075 (.017)	.069 (.016)
Female					
Ten/10	.174 (.052)	.214 (.049)	.248 (.042)	.258 (.041)	.279 (.038)
$Ten^2/10^2$	-.127 (.045)	-.149 (.043)	-.184 (.037)	-.187 (.036)	-.203 (.033)
$Ten^3/10^3$	.025 (.010)	.026 (.010)	.036 (.008)	.036 (.008)	.038 (.008)
Exp	.032 (.002)	.029 (.002)	.023 (002)	.022 (.002)	.022 (.002)
Exp^2	-6.485e-4 (4.69e-5)	-5.940e-4 (4.48e-5)	-4.743e-4 (3.86e-5)	-4.479e-4 (3.77e-5)	-4.449e-4 (3.50e-5)
Pseudo R^2	.234	.316	.363	.393	.396
T5	.058 (.017)	.073 (.016)	.082 (.014)	.087 (.013)	.094 (.012)
T10	.071 (.021)	.090 (.020)	.099 (.017)	.107 (.017)	.115 (.016)
T15	.058 (.021)	.072 (.020)	.078 (.017)	.088 (.017)	.091 (.016)

(*Table 2.39* continued)

T20	.037 (.024)	.037 (.022)	.045 (.019)	.056 (.019)	.053 (.018)

Notes: Model 1 includes: age left education, a cubic in employer-tenure, a quadratic in potential labour market experience, dummies for individual's skills and a time trend (Basic Model). Model 2 is the Basic Model plus regional dummies, 1-digit industry dummies and establishment size dummies. Model 3 is the Basic Model plus regional, occupational and qualification dummies. Model 4 is Basic Model plus dummy variables for region, industry and occupation, establishment size and individual's qualifications. Model 5 is Model 4 plus union coverage and union membership dummies. Standard errors presented in brackets.

Table 2.40

Quantile (Median) Estimates on Tenure Effect: Wage Treatment Over Time

	T 5	T 10	T 15	T 20	Pseudo R^2
Pooled					
Male full-time employees					
Time Trend	.044 (.015)	.062 (.020)	.061 (.020)	.052 (.020)	.269
Wave Dummies	.044 (.015)	.061 (.020)	.059 (.021)	.049 (.021)	.269
Real Wage (R.P.I.)	.049 (.014)	.067 (.019)	.066 (.019)	.055 (.019)	.256
Real Wage (R.P.I.) plus Time Trend	.050 (.014)	.069 (.019)	.067 (.020)	.055 (.020)	.256
Real Wage (A.E.I.)	.037 (.014)	.051 (.019)	.049 (.019)	.040 (.020)	.253
Real Wage (A.E.I.) plus Time Trend	.050 (.015)	.069 (.021)	.068 (.021)	.056 (.021)	.255
Female full-time employees					
Time Trend	.058 (.017)	.071 (.021)	.058 (.021)	.037 (.024)	.234
Wave Dummies	.059 (.015)	.072 (.019)	.058 (.019)	.035 (.021)	.235
Real Wage (R.P.I.)	.068 (.016)	.085 (.020)	.071 (.020)	.046 (.022)	.213
Real Wage (R.P.I.) plus Time Trend	.056 (.016)	.069 (.020)	.056 (.021)	.035 (.023)	.215
Real Wage (A.E.I.)	.054 (.016)	.064 (.020)	.050 (.020)	.028 (.022)	.211
Real Wage (A.E.I.) plus Time Trend	.053 (.016)	.063 (.020)	.049 (.020)	.028 (.023)	.211

Notes: Basic model includes age left education, cubic in tenure, quadratic in potential labour market experience and skill dummies. Standard errors presented in brackets.

Table 2.41

Quantile (Median) Estimates on Tenure Effect: Actual and Potential Experience					
	T5	T10	T15	T20	Pseudo R^2
Male full-time employees					
Pooled					
Potential labour market experience	.044 (.015)	.062 (.020)	.061 (.020)	.052 (.020)	.269
Actual labour market experience	.037 (.014)	.051 (.019)	.051 (.020)	.044 (.020)	.268
Unbalanced					
Potential labour market experience	.047 (.014)	.065 (.019)	.064 (.019)	.053 (.019)	.269
Actual labour market experience	.042 (.014)	.057 (.019)	.057 (.019)	.048 (.020)	.268
Balanced					
Potential labour market experience	.002 (.020)	-.007 (.027)	-.019 (.028)	-.021 (.027)	.276
Actual labour market experience	-.002 (.020)	-.013 (.027)	-.023 (.028)	-.023 (.027)	.274
Female full-time employees					
Pooled					
Potential labour market experience	.058 (.017)	.071 (.021)	.058 (.021)	.037 (.024)	.234
Actual labour market experience	.033 (.017)	.015 (.021)	-.028 (.021)	-.072 (.024)	.241
Unbalanced					
Potential labour market experience	.049 (.018)	.059 (.022)	.046 (.022)	.026 (.024)	.235
Actual labour market experience	.027 (.016)	.008 (.020)	-.036 (.021)	-.078 (.023)	.241
Balanced					
Potential labour market experience	.021 (.024)	.010 (.030)	-.018 (.030)	-.046 (.030)	.217
Actual labour market experience	.049 (.026)	.031 (.033)	-.023 (.032)	-.086 (.033)	.230

Notes: Basic model includes age left education, cubic in tenure, quadratic in labour market experience, skill dummies and a time trend. Actual labour market experience refers to full-time employment only. Standard errors presented in brackets.

Table 2.42

Robust Standard Error Estimates Tenure Effect					
	Model 1	Model 2	Model 3	Model 4	Model 5
Male					
$Ten/10$	.145 (.032)	.111 (.029)	.173 (.030)	.150 (.028)	.147 (.028)
$Ten^2/10^2$	-.082 (.023)	-.064 (.021)	-.094 (.021)	-.087 (.020)	-.089 (.020)
$Ten^3/10^3$	.013 (.004)	.011 (.004)	.016 (.004)	.015 (.004)	.016 (.004)
Exp	.038 (.002)	.035 (.002)	.036 (.002)	.032 (.001)	.032 (.001)
Exp^2	-.6.481e-4 (3.45e-5)	-6.016e-4 (3.21e-5)	-5.997e-4 (3.27e-5)	-5.350e-4 (3.10e-5)	-5.261e-4 (3.09e-5)
F-stat.	479.64	195.09	166.89	158.82	154.64
T5	.055 (.011)	.041 (.010)	.065 (.010)	.055 (.010)	.053 (.010)
T10	.079 (.015)	.059 (.014)	.095 (.014)	.078 (.013)	.074 (.013)
T15	.083 (.015)	.061 (.014)	.103 (.014)	.080 (.014)	.074 (.014)
T20	.075 (.015)	.056 (.014)	.099 (.015)	.073 (.014)	.064 (.014)
Female					
$Ten/10$	.193 (.046)	.220 (.042)	.261 (.038)	.272 (.037)	.280 (.037)
$Ten^2/10^2$	-.160 (.040)	-.164 (.036)	-.188 (.033)	-.188 (.032)	-.197 (.032)
$Ten^3/10^3$	.033 (.009)	.031 (.008)	.037 (.008)	.036 (.007)	.038 (.007)
Exp	.032 (.002)	.030 (.002)	.022 (.002)	.022 (.001)	.021 (.001)
Exp^2	-.6.525e-4 (4.11e-5)	-5.939e-4 (3.78e-5)	-4.597e-4 (3.47e-5)	-4.303e-4 (3.35e-5)	-4.289e-4 (3.34e-5)
F-stat.	318.24	135.16	163.77	142.98	140.09
T5	.061 (.015)	.073 (.013)	.088 (.012)	.094 (.012)	.095 (.012)
T10	.066 (.018)	.087 (.017)	.110 (.015)	.120 (.015)	.120 (.015)
T15	.042 (.019)	.066 (.017)	.092 (.016)	.106 (.015)	.103 (.015)
T20	.013 (.021)	.032 (.019)	.064 (.017)	.078 (.017)	.071 (.017)

Notes: Model 1 includes: age left education, a cubic in employer-tenure, a quadratic in potential labour market experience, dummies for individual's skills and a time trend (Basic Model). Model 2 is the Basic Model plus regional dummies, 1-digit industry dummies and establishment size dummies. Model 3 is the Basic Model plus regional, occupational and qualification dummies. Model 4 is Basic Model plus dummy variables for region, industry and occupation, establishment size and individual's qualifications. Model 5 is Model 4 plus union coverage and union membership dummies. Standard errors presented in brackets.

Table 2.43

Quantile Regressions: Tenure Effect				
Quantile	I	II	III	IV
Male				
.10	.183 (.024)	.165 (.025)	.195 (.024)	.161 (.024)
.20	.142 (.020)	.093 (.022)	.158 (.022)	.102 (.021)
.30	.107 (.017)	.077 (.016)	.113 (.015)	.086 (.015)
.40	.070 (.017)	.052 (.017)	.091 (.017)	.086 (.016)
.50	.062 (.020)	.044 (.019)	.076 (.017)	.078 (.015)
.60	.070 (.016)	.040 (.016)	.082 (.017)	.063 (.014)
.70	.048 (.020)	.043 (.016)	.072 (.017)	.058 (.014)
.80	.053 (.021)	.044 (.016)	.052 (.017)	.038 (.016)
.90	.040 (.023)	.043 (.021)	.058 (.022)	.061 (.025)
OLS	.094 (.016)	.076 (.015)	.110 (.015)	.091 (.014)
Female				
.10	.008 (.035)	.103 (.025)	.124 (.029)	.126 (.027)
.20	.061 (.029)	.094 (.029)	.125 (.020)	.130 (.017)
.30	.083 (.024)	.090 (.023)	.119 (.019)	.114 (.019)
.40	.080 (.021)	.088 (.018)	.101 (.017)	.112 (.016)
.50	.071 (.021)	.090 (.020)	.099 (.017)	.115 (.016)
.60	.068 (.023)	.077 (.018)	.109 (.016)	.105 (.015)
.70	.073 (.023)	.080 (.020)	.120 (.016)	.119 (.019)
.80	.062 (.020)	.062 (.020)	.094 (.021)	.110 (.019)
.90	.063 (.027)	.070 (.029)	.057 (.027)	.126 (.023)
OLS	.064 (.020)	.090 (.018)	.109 (.018)	.128 (.017)

Notes: **Model I** includes: age left education, a cubic in employer-tenure, a quadratic in potential labour market experience, dummies for individual's skills and a time trend (Basic Model). **Model II** is the Basic Model plus regional dummies, 1-digit industry dummies and establishment size dummies. **Model III** is the Basic Model plus regional, occupational and qualification dummies. **Model IV** is Basic Model plus dummy variables for region, industry and occupation, establishment size, individual's qualifications, union coverage and union membership. Estimated ten-year tenure effect with standard errors in brackets.

Table 2.44

Interquantile Regressions
Testing Equality of Tenure Effect Between Quantiles

Quantiles		I	II	III	IV
Male					
0.10	0.25	.004	.000	.010	.008
0.10	0.40	.000	.000	.000	.030
0.10	0.50	.000	.000	.000	.001
0.10	0.60	.000	.000	.000	.000
0.10	0.75	.000	.000	.000	.000
0.10	0.90	.000	.001	.001	.003
0.25	0.40	.008	.057	.016	.510
0.25	0.50	.010	.019	.000	.427
0.25	0.60	.040	.010	.012	.125
0.25	0.75	.033	.054	.000	.024
0.25	0.90	.006	.217	.017	.190
0.40	0.50	.504	.369	.227	.386
0.40	0.60	.992	.345	.523	.167
0.40	0.75	.201	.768	.057	.030
0.40	0.90	.205	.766	.130	.256
0.50	0.60	.534	.656	.691	.186
0.50	0.75	.558	.972	.578	.139
0.50	0.90	.471	.930	.430	.439
0.60	0.75	.212	.709	.362	.366
0.60	0.90	.181	.923	.318	.938
0.75	0.90	.546	.891	.671	.623
Female					
0.10	0.25	.000	.738	.832	.596
0.10	0.40	.014	.689	.495	.649
0.10	0.50	.054	.677	.435	.692
0.10	0.60	.178	.460	.635	.576
0.10	0.75	.032	.402	.691	.881
0.10	0.90	.133	.432	.107	.985
0.25	0.40	.896	.874	.358	.897
0.25	0.50	.822	.966	.366	.999
0.25	0.60	.999	.516	.718	.713
0.25	0.75	.823	.405	.831	.694
0.25	0.90	.735	.581	.040	.648
0.40	0.50	.560	.889	.901	.840
0.40	0.60	.673	.436	.616	.570
0.40	0.75	.861	.574	.666	.617
0.40	0.90	.573	.662	.142	.556
0.50	0.60	.816	.334	.528	.186
0.50	0.75	.556	.373	.519	.740
0.50	0.90	.794	.503	.014	.640
0.60	0.75	.516	.868	.918	.273
0.60	0.90	.877	.858	.041	.303
0.75	0.90	.449	.833	.052	.837

Notes: Model I includes: age left education, a cubic in employer-tenure, a quadratic in potential labour market experience, dummies for individual's skills and a time trend (Basic Model). Model II is the Basic Model plus regional dummies, 1-digit industry dummies and establishment size dummies. Model III is the Basic Model plus regional, occupational and qualification dummies. Model IV is Basic Model plus dummy variables for region, industry and occupation, establishment size, individual's qualifications, union coverage and union membership. P-values of performed tests of equality between tenure effect estimated at different quantiles.

Table 2.45

Quantile	I	II	III	IV
	IV-Quantile Regressions: Tenure Effect			
Male				
.10	.116	.147	.155	.138
	(.063)	(.051)	(.059)	(.047)
.20	.100	.074	.073	.121
	(.047)	(.038)	(.034)	(.040)
.30	.071	.078	.052	.113
	(.043)	(.029)	(.038)	(.034)
.40	3.51e-4	.042	.059	.068
	(.035)	(.039)	(.035)	(.034)
.50	.015	.009	.040	.063
	(.036)	(.041)	(.036)	(.036)
.60	.037	.046	.033	.060
	(.040)	(.038)	(.037)	(.035)
.70	-.003	.039	.050	.037
	(.041)	(.036)	(.035)	(.030)
.80	.045	.059	.056	.057
	(.044)	(.039)	(.038)	(.035)
.90	.079	.081	.026	.095
	(.056)	(.047)	(.052)	(.051)
Female				
.10	-.034	-.025	.050	.078
	(.070)	(.050)	(.064)	(.064)
.20	.003	.003	.021	.039
	(.066)	(.063)	(.052)	(.053)
.30	-.012	.013	.010	.024
	(.049)	(.044)	(.049)	(.045)
.40	-.018	-.008	.026	.009
	(.045)	(.037)	(.036)	(.044)
.50	-.022	-.002	.040	.037
	(.043)	(.037)	(.038)	(.042)
.60	-.043	-.011	.050	.026
	(.051)	(.034)	(.041)	(.037)
.70	-.035	-.017	.043	.012
	(.050)	(.040)	(.033)	(.032)
.80	.007	-.041	-.037	.021
	(.046)	(.038)	(.039)	(.045)
.90	-.029	-.074	-.012	-3.19e-4
	(.059)	(.055)	(.045)	(.035)

Notes: **Model I** includes: age left education, a cubic in employer-tenure, a quadratic in potential labour market experience, dummies for individual's skills and a time trend (Basic Model). **Model II** is the Basic Model plus regional dummies, 1-digit industry dummies and establishment size dummies. **Model III** is the Basic Model plus regional, occupational and qualification dummies. **Model IV** is Basic Model plus dummy variables for region, industry and occupation, establishment size, individual's qualifications, union coverage and union membership. Estimated ten-year tenure effect with standard errors in brackets, based on 2SQR estimator.

Table 2.46

IV-Interquantile Regressions (2SQR)
Testing Equality of Tenure Effect Between Quantiles

Quantiles		I	II	III	IV
Male					
0.10	0.25	.094	.207	.044	.960
0.10	0.40	.042	.041	.027	.122
0.10	0.50	.066	.012	.032	.134
0.10	0.60	.193	.026	.069	.121
0.10	0.75	.082	.096	.128	.117
0.10	0.90	.712	.297	.027	.592
0.25	0.40	.004	.061	.804	.007
0.25	0.50	1.00e-4	.019	.436	.086
0.25	0.60	.094	.357	.382	.040
0.25	0.75	9.00e-4	.165	.939	.100
0.25	0.90	.060	.826	.464	.435
0.40	0.50	.057	.607	.366	.859
0.40	0.60	.033	.929	.495	.864
0.40	0.75	.062	..885	.885	.611
0.40	0.90	.195	.501	.283	.626
0.50	0.60	.412	.172	.815	.913
0.50	0.75	.896	.543	.613	.595
0.50	0.90	.217	.154	.799	.510
0.60	0.75	.614	.758	.447	.621
0.60	0.90	.477	.317	.884	.512
0.75	0.90	.166	.389	.242	.381
Female					
0.10	0.25	.768	.170	.674	.231
0.10	0.40	.817	.744	.748	.172
0.10	0.50	.722	.744	.899	.521
0.10	0.60	.912	.817	.999	.343
0.10	0.75	.796	.862	.602	.427
0.10	0.90	.963	.586	.380	.314
0.25	0.40	.990	.450	.900	.515
0.25	0.50	.939	.636	.687	.939
0.25	0.60	.583	.492	.553	.893
0.25	0.75	.953	.352	851	.730
0.25	0.90	.908	.267	.647	.494
0.40	0.50	.908	.850	.683	.257
0.40	0.60	.597	.933	.500	.597
0.40	0.75	.968	.594	.793	.993
0.40	0.90	.899	.329	.302	.869
0.50	0.60	.500	.752	.707	.564
0.50	0.75	.889	.518	.402	.494
0.50	0.90	.913	.378	.385	.604
0.60	0.75	.521	.647	.326	.720
0.60	0.90	.840	.446	.166	.641
0.75	0.90	.861	.489	.580	.855

Notes: Model I includes: age left education, a cubic in employer-tenure, a quadratic in potential labour market experience, dummies for individual's skills and a time trend (Basic Model). Model II is the Basic Model plus regional dummies, 1-digit industry dummies and establishment size dummies. Model III is the Basic Model plus regional, occupational and qualification dummies. Model IV is Basic Model plus dummy variables for region, industry and occupation, establishment size, individual's qualifications, union coverage and union membership. P-values of performed tests of equality between tenure effect estimated at different quantiles.

Chapter 2: Figures

Male

Figure 2.1.a

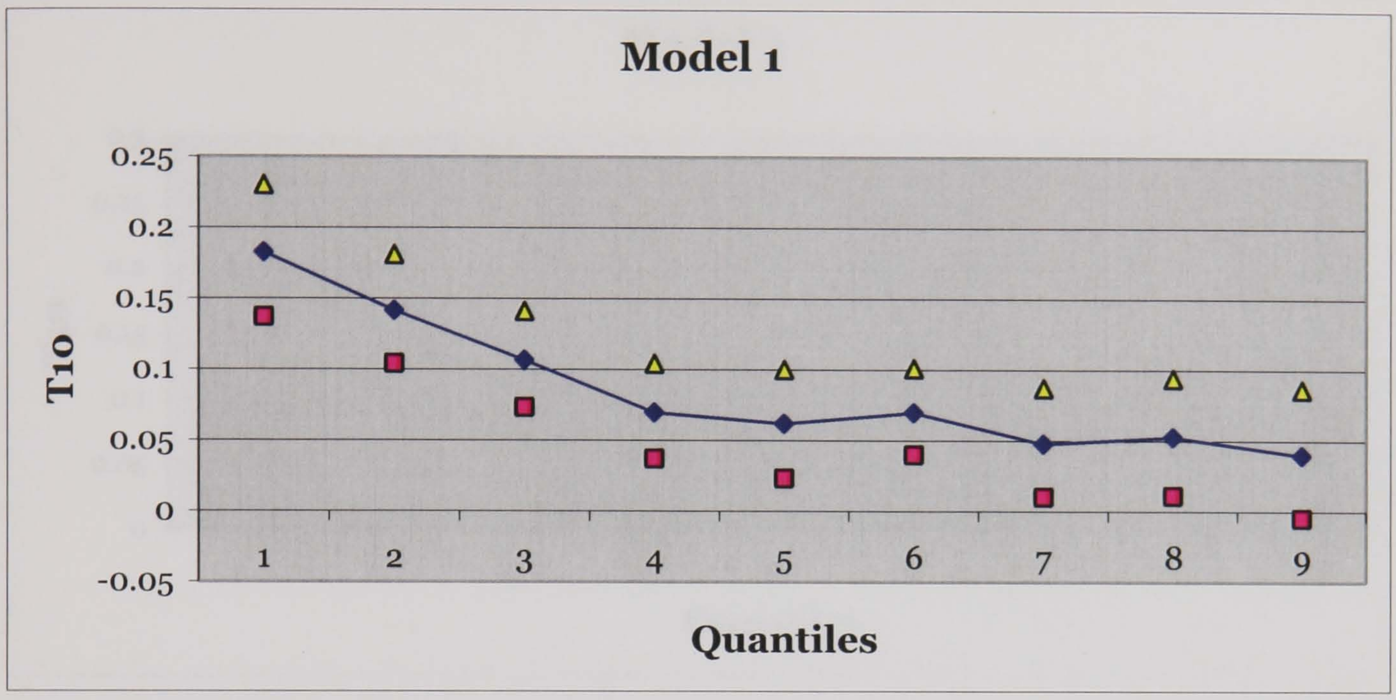


Figure 2.1.b

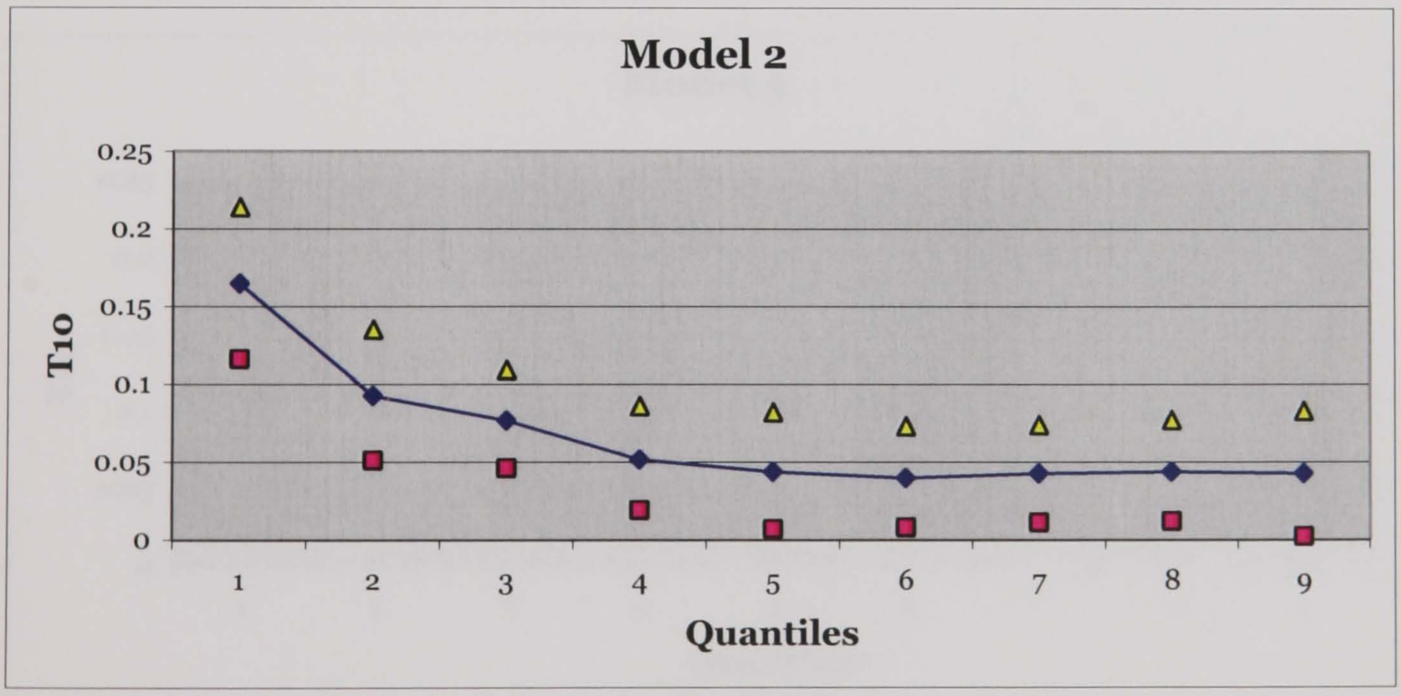


Figure 2.1.c

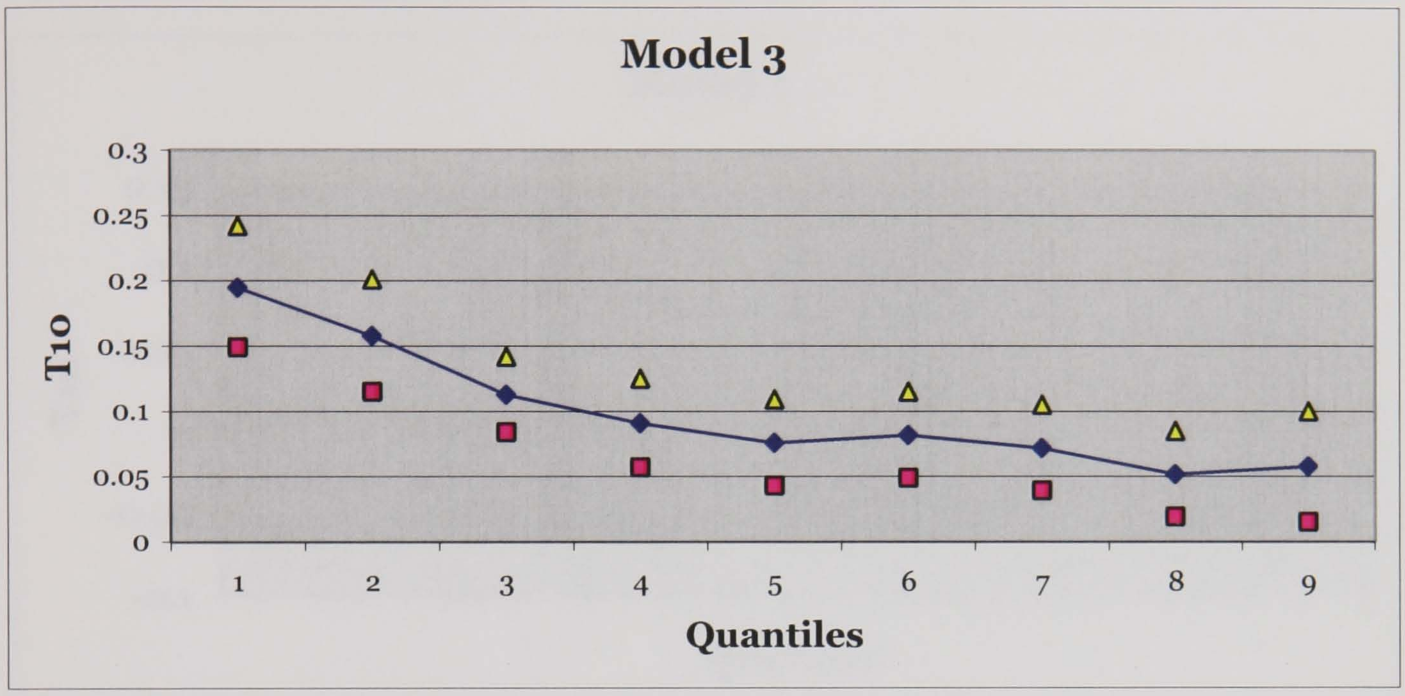
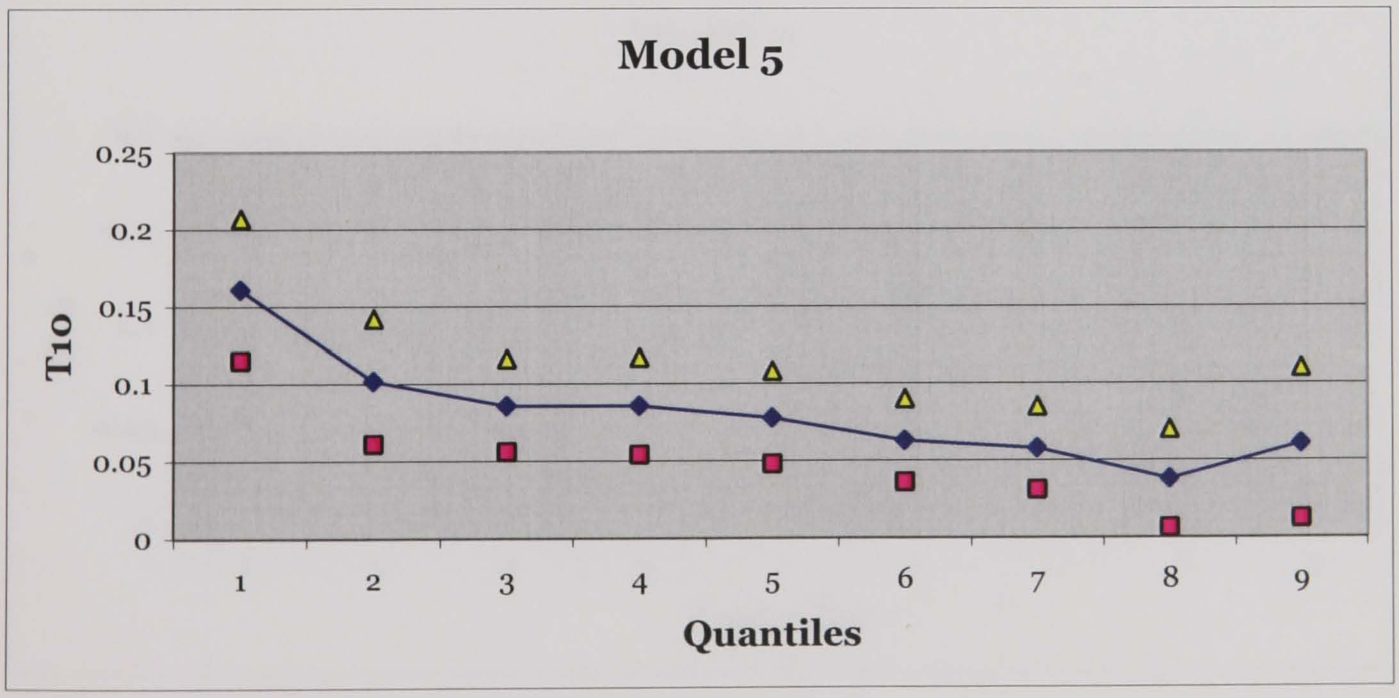


Figure 2.1.d



Female

Figure 2.2.a

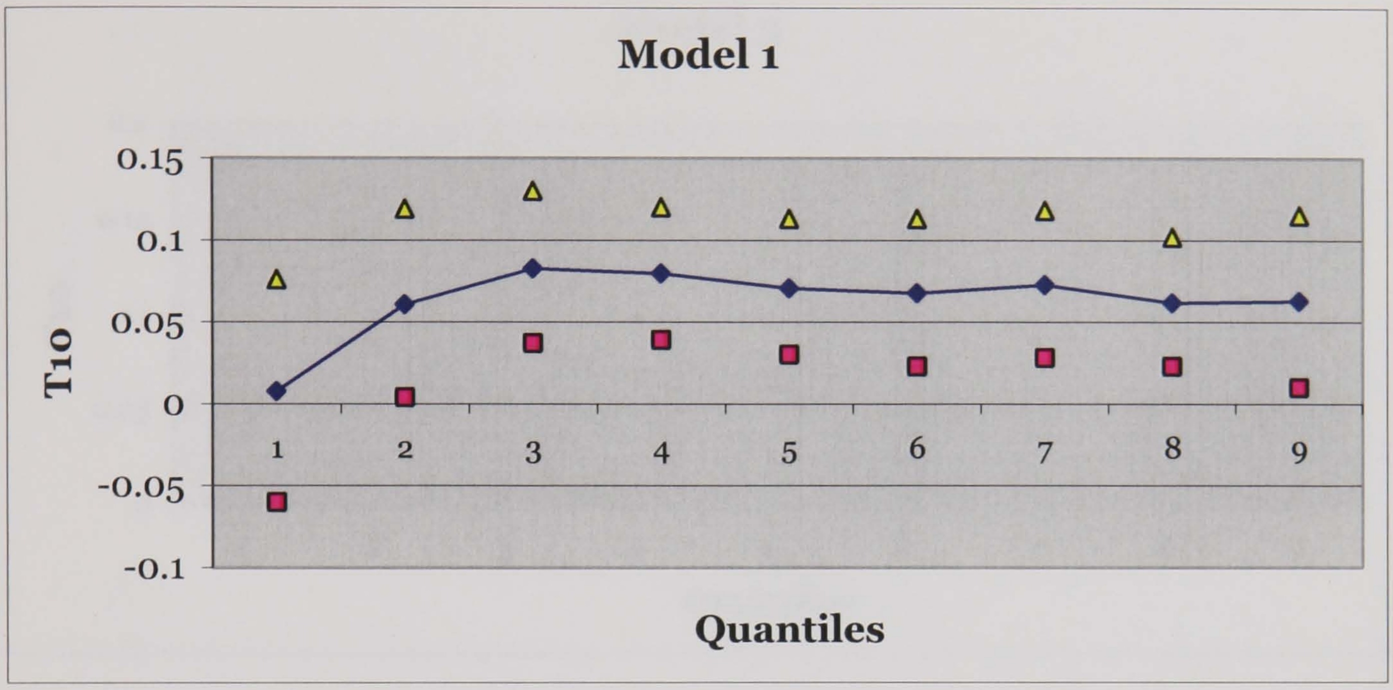


Figure 2.2.b

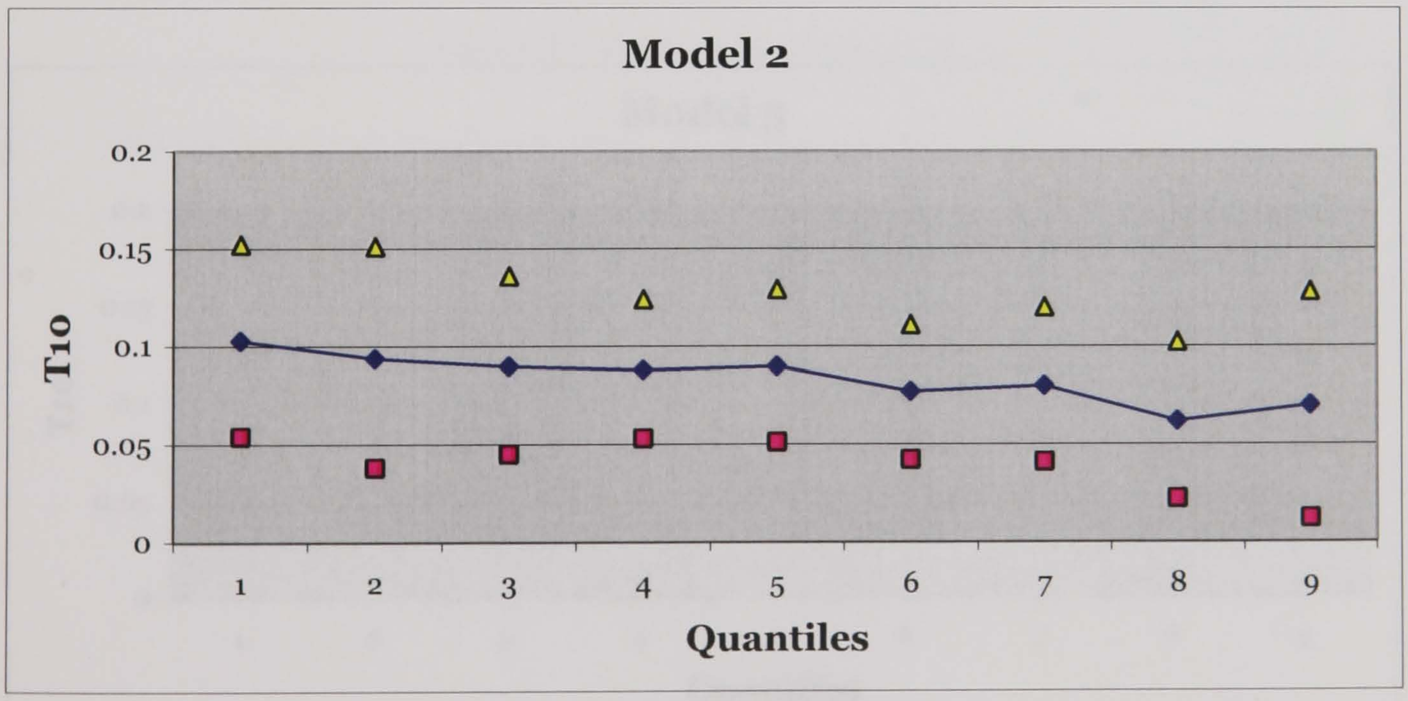


Figure 2.2.c

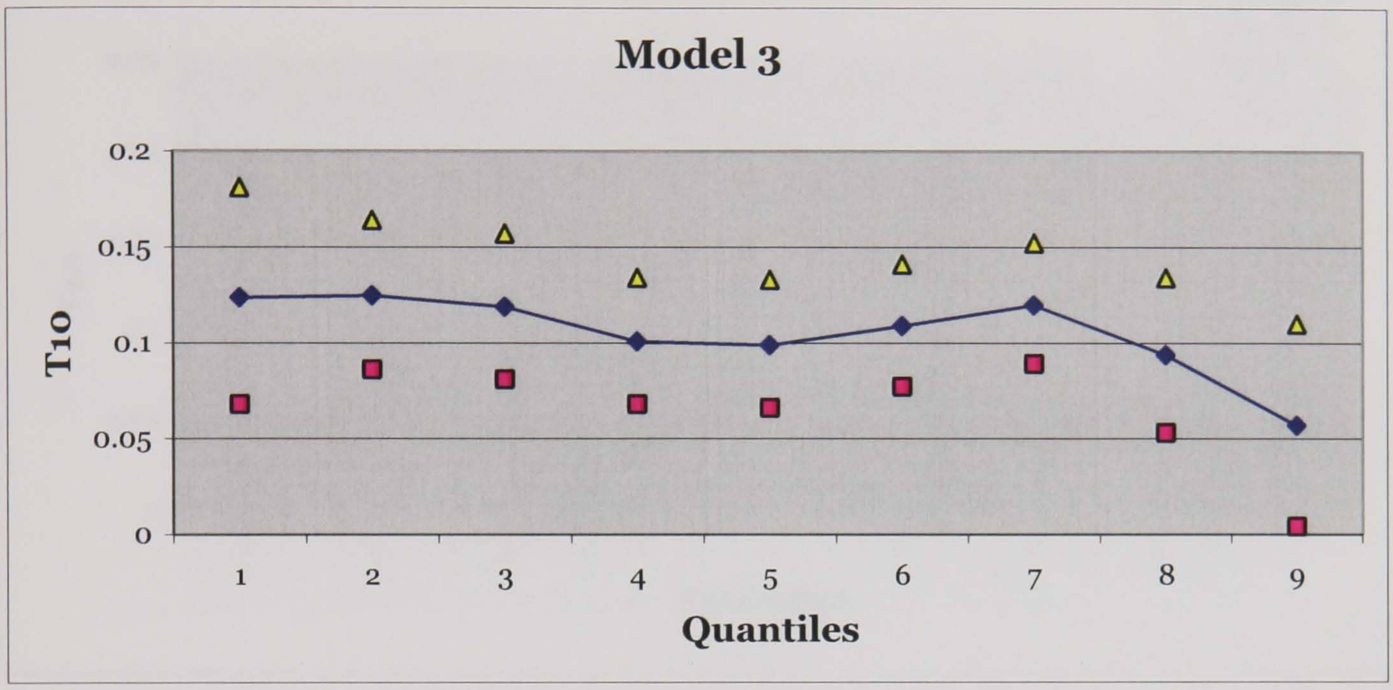


Figure 2.2.d

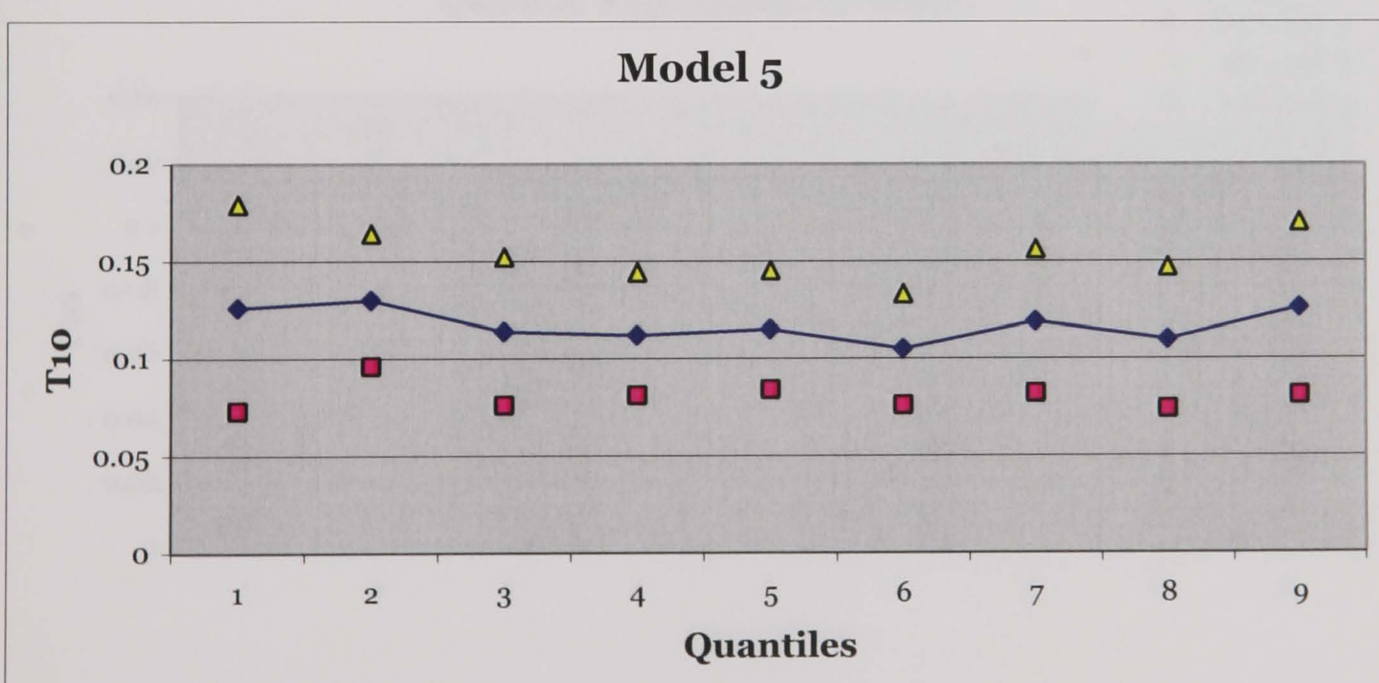


Figure 2.3

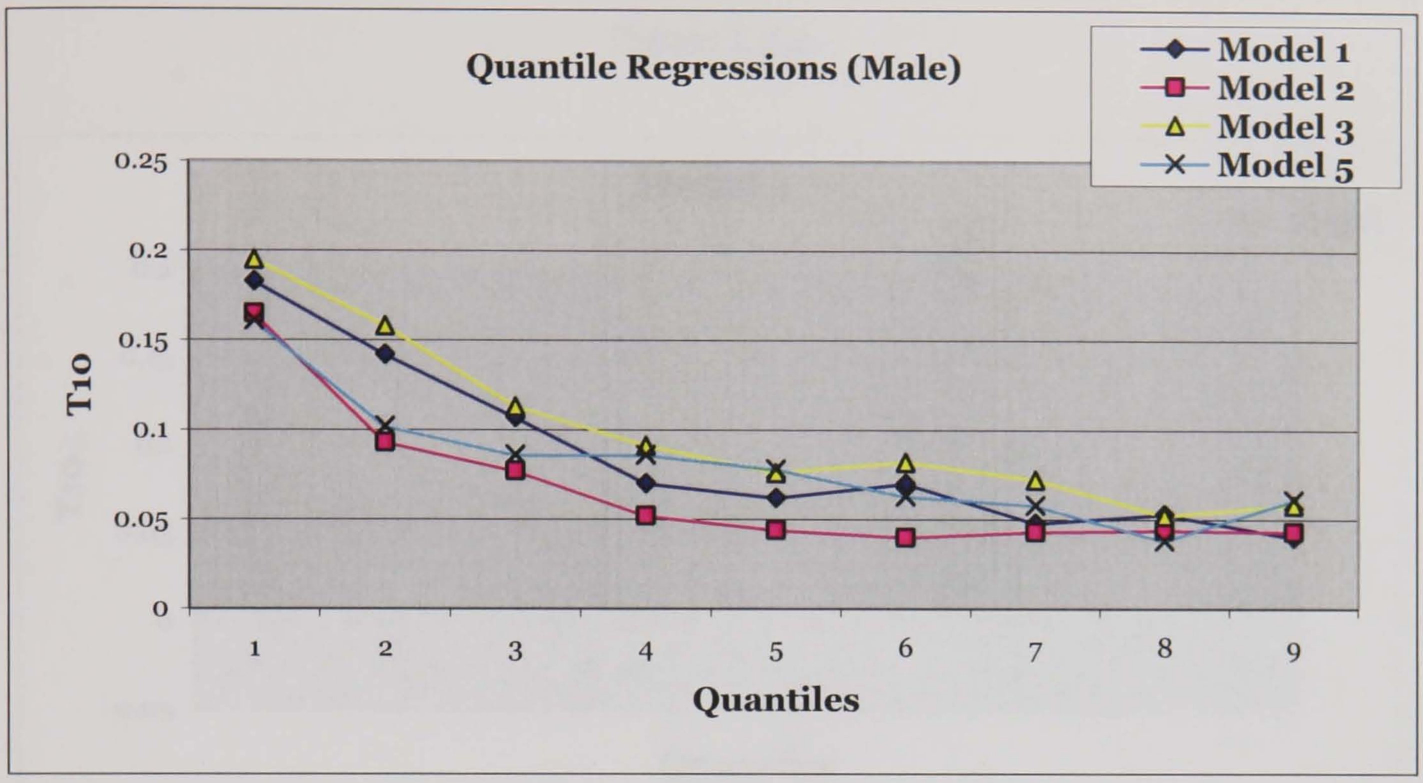
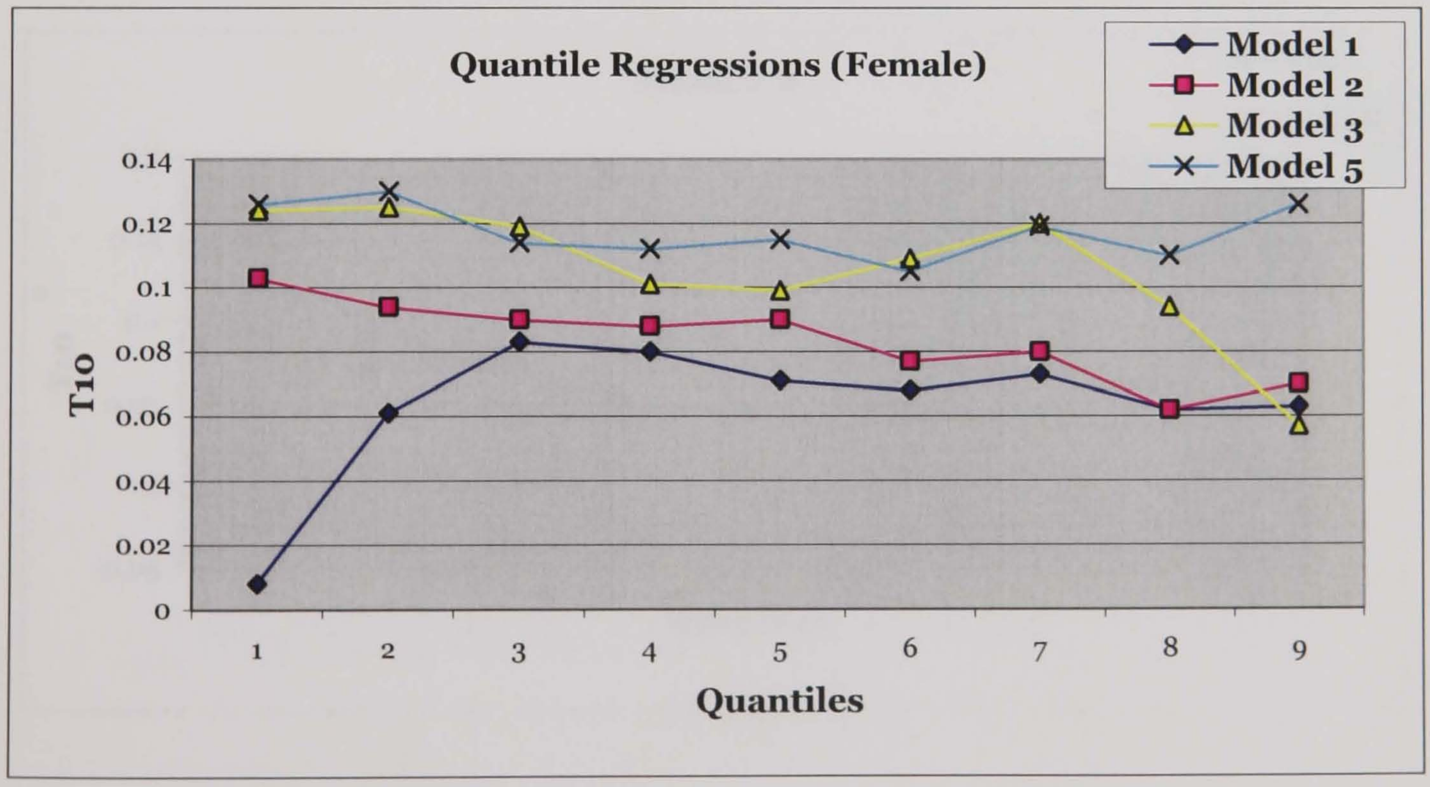


Figure 2.4



Male

Figure 2.5.a

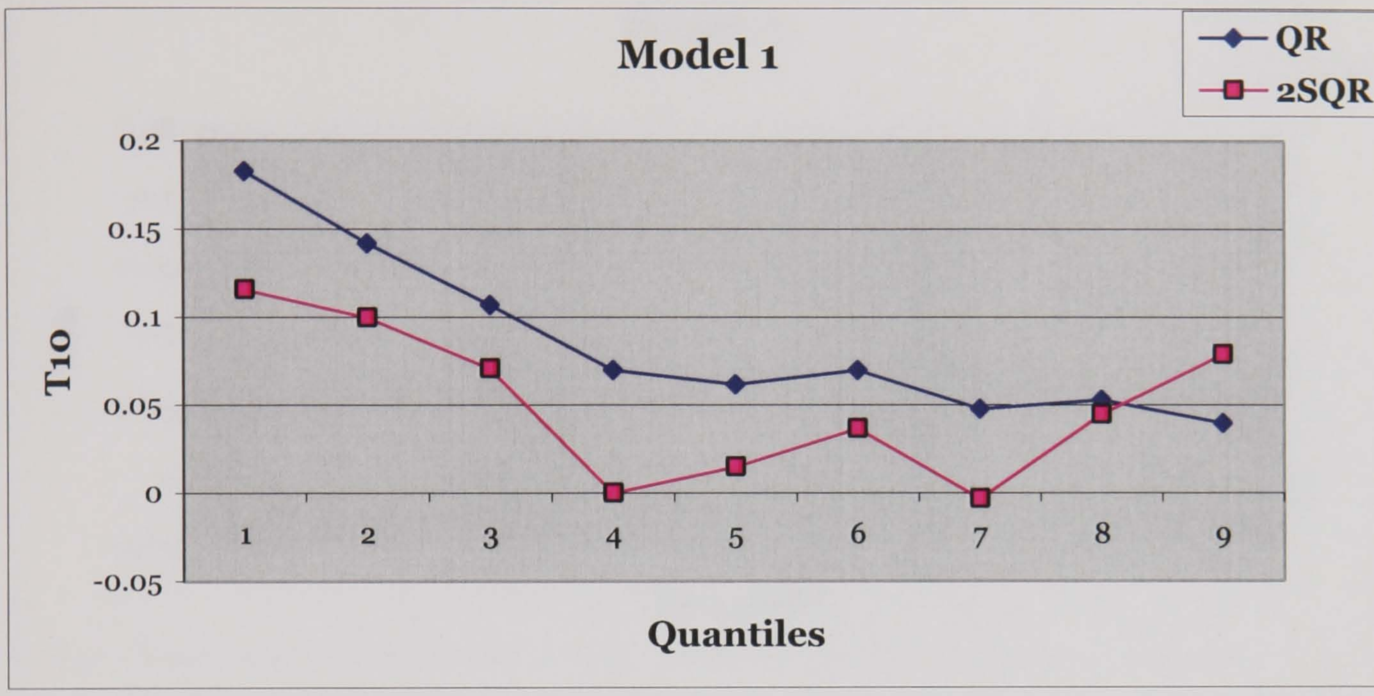


Figure 2.5.b

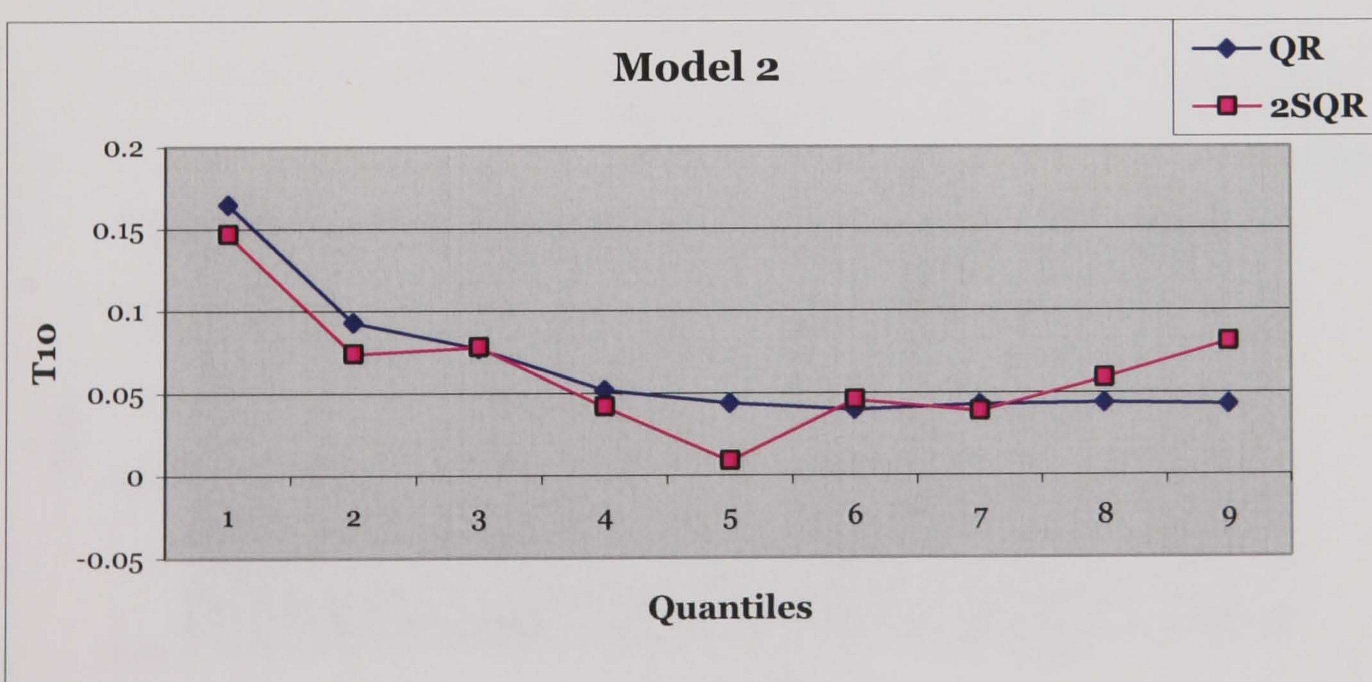


Figure 2.5.c

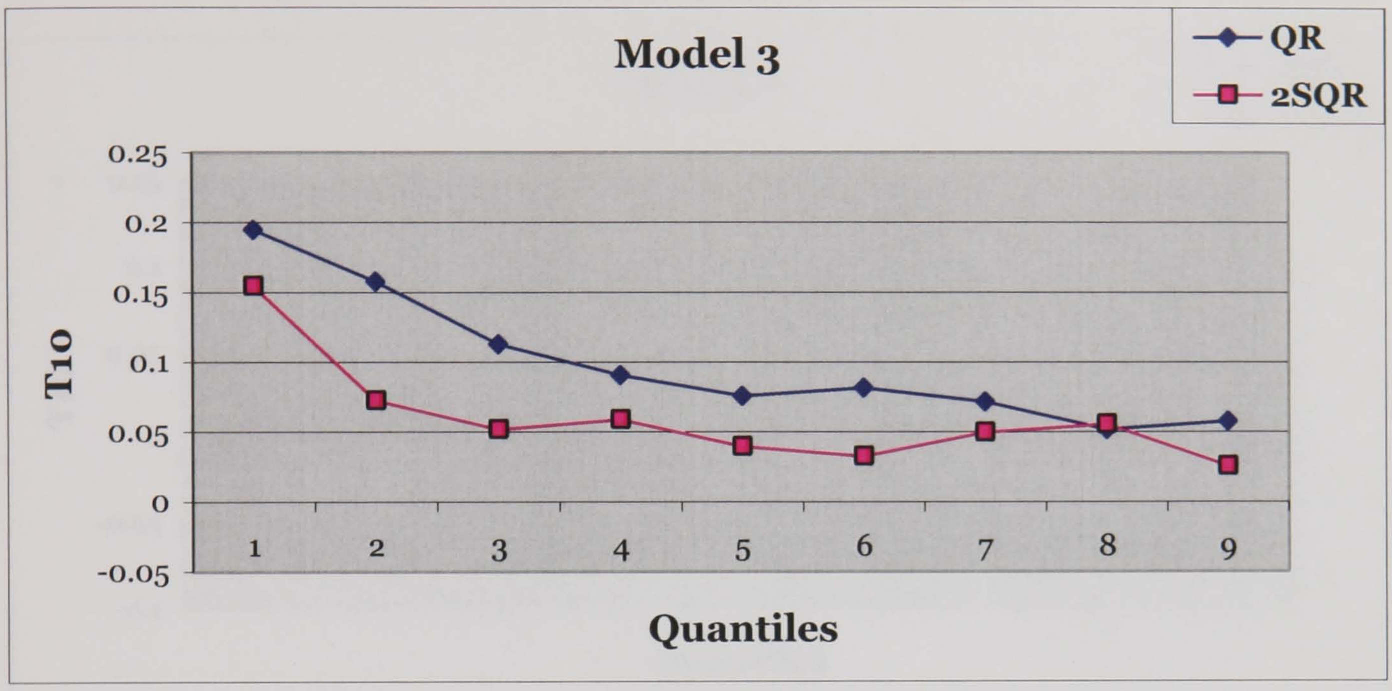
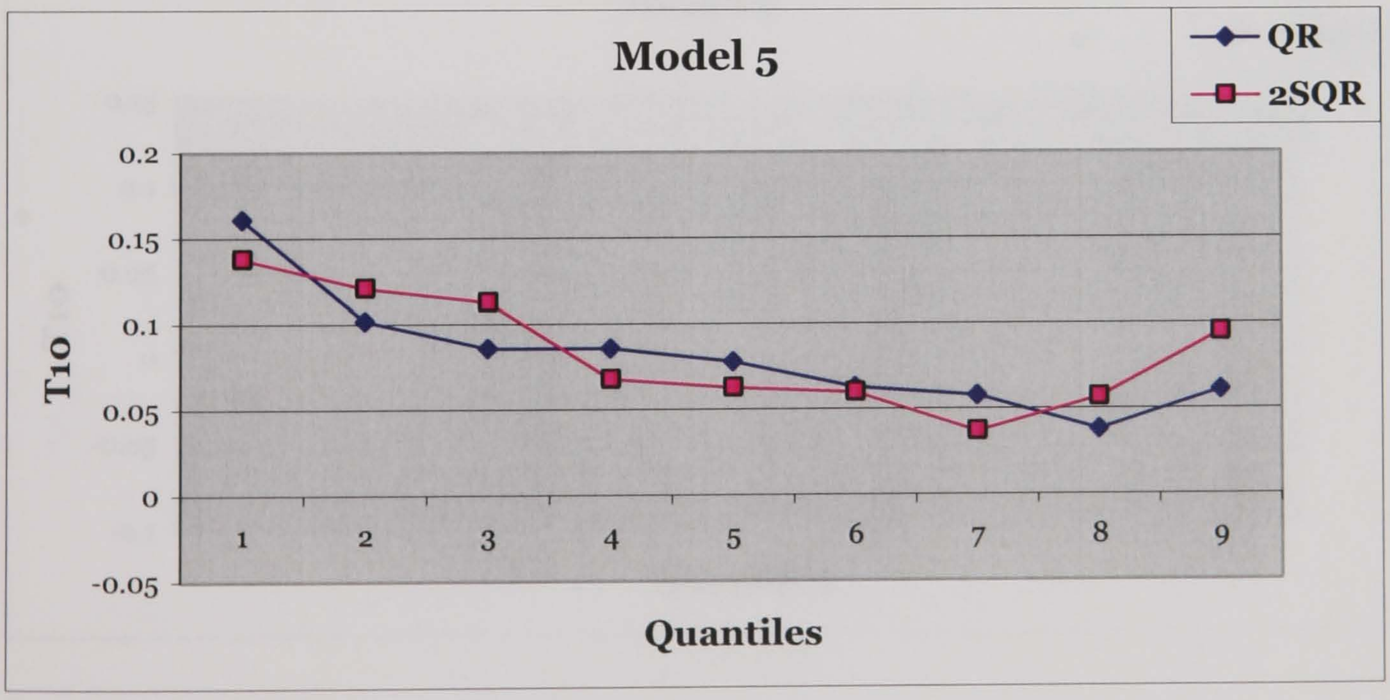


Figure 2.5.d



Female

Figure 2.6.a

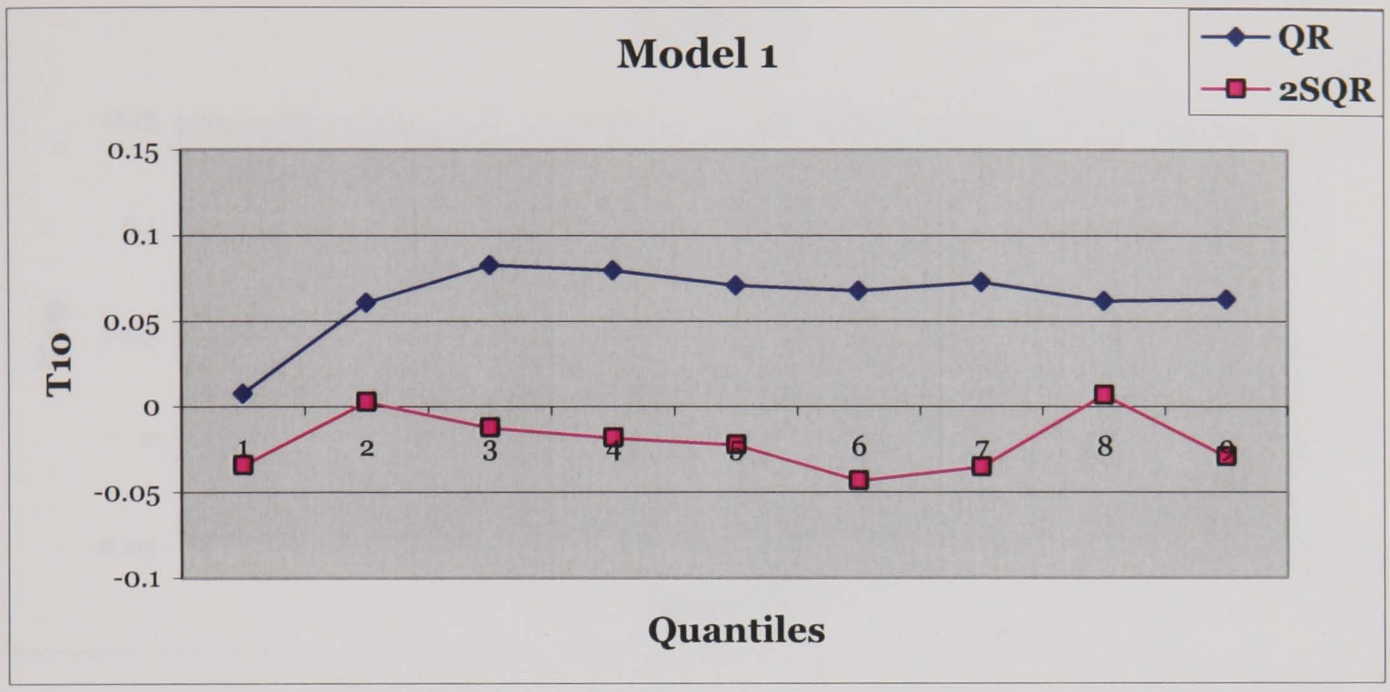


Figure 2.6.b

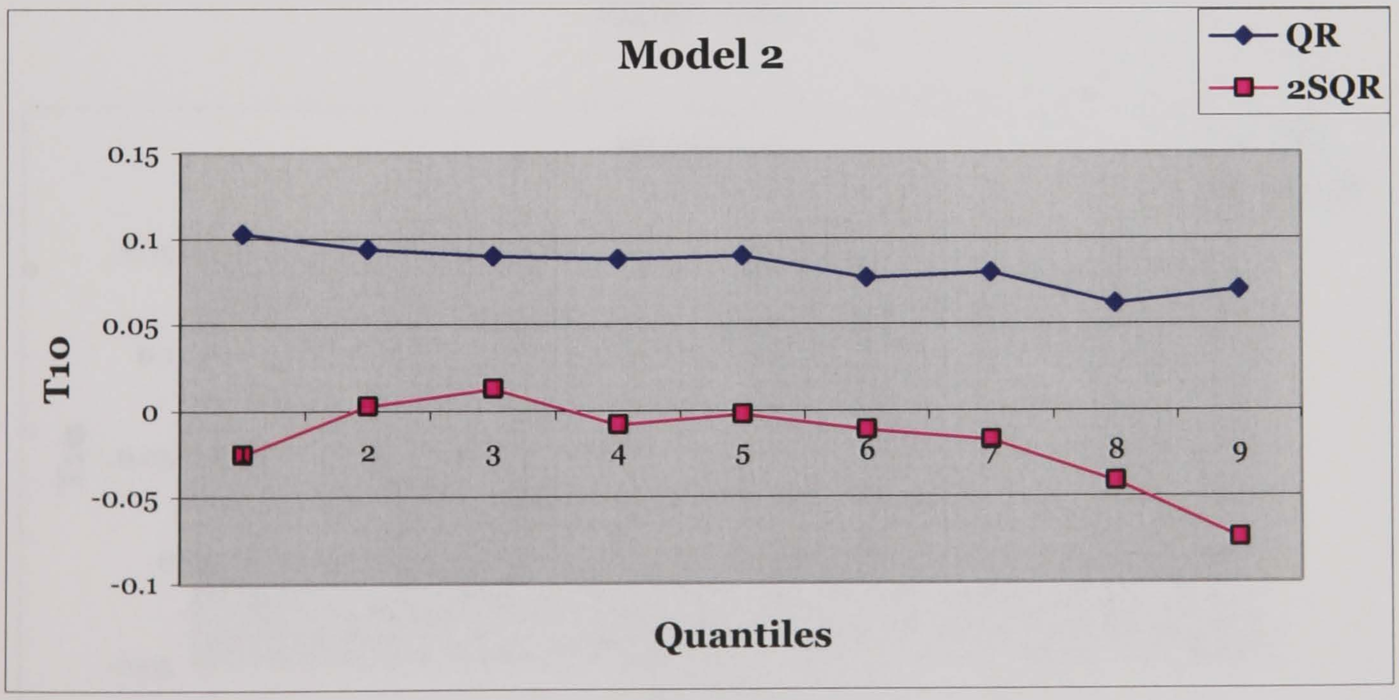


Figure 2.6.c

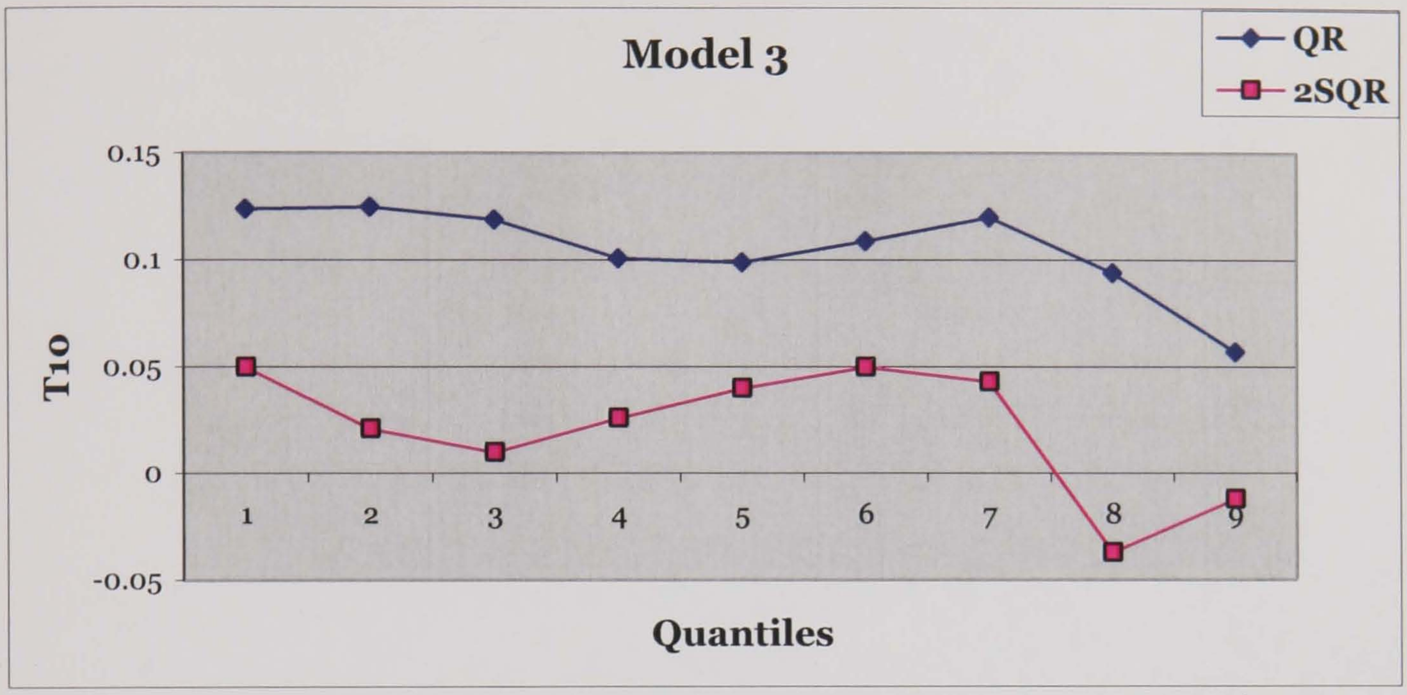
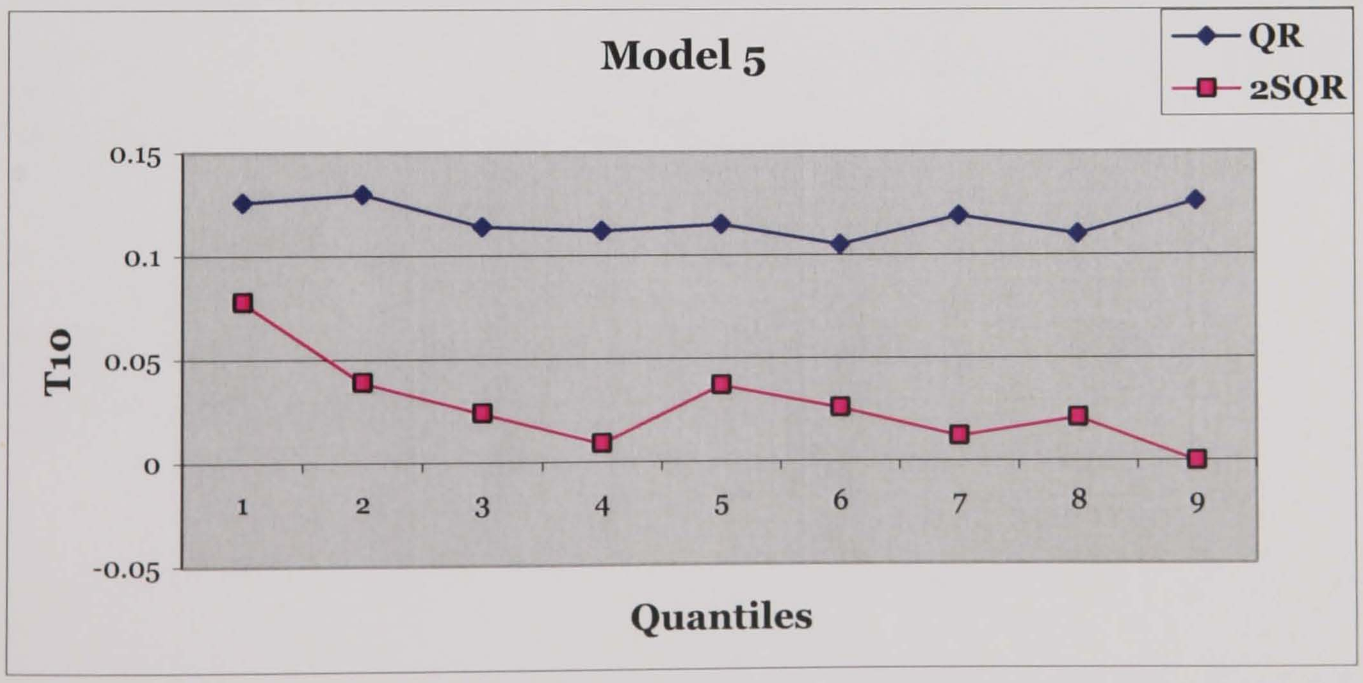


Figure 2.6.d



Chapter 2: Appendix

Table A.2.1

BHPS Coverage Period	
Wave 1	3rd September 1991 to 30th January 1992
Wave 2	5th September 1992 to 30th April 1993
Wave 3	5th September 1993 to 30th April 1994
Wave 4	3rd September 1994 to 9th May 1995
Wave 5	4th September 1995 to 30th April 1996
Wave 6	29th August 1996 to 17th April 1997
Wave 7	29th August 1997 to 8th May 1998
Wave 8	1st September 1998 to 8th May 1999

Table A.2.2

BHPS Sample Characteristics (Waves 1-8)

	Pooled Sample		Unbalanced Panel Sample		Balanced Panel Sample	
	Male	Female	Male	Female	Male	Female
Age	38.63 (10.29)	38.06 (10.59)	38.68 (10.25)	38.17 (10.56)	39.69 (9.38)	40.15 (9.77)
Employer Tenure	7.53 (7.05)	6.14 (5.62)	7.57 (7.04)	6.20 (5.62)	9.30 (6.96)	7.57 (5.97)
Actual Labour Market Experience (Full-time)	20.57 (10.99)	14.19 (8.34)	20.63 (10.96)	14.27 (8.33)	22.14 (9.96)	15.70 (8.07)
Actual Labour Market Experience (Part-time)	0.51 (2.20)	3.07 (4.94)	0.50 (2.18)	3.09 (4.96)	0.33 (1.60)	3.54 (5.11)
Potential Labour Market Experience	21.29 (10.88)	20.66 (11.34)	21.33 (10.84)	20.77 (11.29)	22.45 (9.93)	22.90 (10.61)
Hourly Wage Rate (Nominal Values)	8.49 (6.09)	6.70 (3.65)	8.52 (6.11)	6.72 (3.65)	8.66 (5.66)	7.00 (3.94)
Sample	7638	5398	7518	5628	3168	2232

Notes: Reported means with standard deviation into brackets.

Table A.2.3

BHPS Sample Characteristics: Male Employees							
	Sample	Age	Employer Tenure	Actual Labour Market Experience (Full-time)	Actual Labour Market Experience (Part-time)	Potential Labour Market Experience	Hourly Wage Rate (Nominal Values)
Wave 1	1237	37.35 (10.65)	6.73 (7.19)	19.44 (11.31)	0.48 (2.35)	20.05 (11.48)	7.28 (3.88)
Wave 2	1329	37.47 (10.68)	6.83 (6.78)	19.59 (11.29)	0.43 (2.07)	20.17 (11.43)	7.72 (4.36)
Wave 3	1012	37.88 (10.46)	7.09 (6.84)	19.90 (11.13)	0.43 (1.91)	20.46 (11.09)	8.03 (4.57)
Wave 4	956	38.42 (10.36)	7.52 (7.21)	20.33 (11.12)	0.51 (2.21)	21.11 (10.86)	8.53 (5.46)
Wave 5	928	38.97 (9.97)	7.69 (7.17)	20.83 (10.79)	0.54 (2.35)	21.66 (10.43)	8.84 (5.25)
Wave 6	853	39.51 (9.69)	7.82 (6.93)	21.23 (10.51)	0.59 (2.38)	22.14 (10.13)	9.48 (7.82)
Wave 7	729	40.66 (9.59)	8.78 (7.03)	22.36 (10.43)	0.60 (2.18)	23.24 (10.08)	9.52 (5.37)
Wave 8	594	41.27 (9.35)	9.36 (6.91)	23.07 (10.18)	0.59 (2.07)	23.95 (9.79)	10.27 (11.96)

Notes: Reported means with standard deviation into brackets.

Table A.2.4

BHPS Sample Characteristics: Female Employees								
	Sample	Age	Employer Tenure	Actual Labour Market Experience (Full-time)	Actual Labour Market Experience (Part-time)	Potential Labour Market Experience	Hourly Wage Rate (Nominal Values)
Wave 1	868	36.00 (10.85)	4.99 (5.60)	12.79 (8.50)	2.62 (4.71)	18.50 (11.70)	5.73 (2.86)
Wave 2	935	35.94 (10.97)	5.21 (5.39)	12.70 (8.30)	2.73 (4.80)	18.52 (11.79)	5.98 (3.02)
Wave 3	737	37.17 (10.60)	5.65 (5.33)	13.42 (8.30)	3.04 (5.00)	19.75 (11.35)	6.33 (3.31)
Wave 4	683	38.02 (10.44)	6.12 (5.43)	14.18 (8.32)	3.05 (5.00)	20.58 (11.13)	6.65 (3.31)
Wave 5	636	38.82 (10.02)	6.51 (5.49)	14.61 (8.04)	3.20 (5.03)	21.45 (10.69)	7.12 (3.69)
Wave 6	593	39.58 (9.91)	6.72 (5.74)	15.24 (7.96)	3.31 (5.01)	22.19 (10.60)	7.44 (3.80)
Wave 7	516	40.61 (9.93)	7.41 (5.60)	16.18 (8.05)	3.44 (4.97)	23.32 (10.63)	7.78 (5.29)
Wave 8	430	42.14 (9.68)	8.53 (5.82)	17.12 (8.02)	3.81 (5.10)	24.90 (10.41)	7.97 (3.73)

Notes: Reported means with standard deviation into brackets.

Table A.2.5

	Nominal and Real Average Hourly Wage Rates							
	Nominal Hourly Wage		Deflated Hourly Wage (RPI)		De-trended Hourly Wage (AEI)		RPI	AEI
Year	Male	Female	Male	Female	Male	Female		
1991	7.28 (3.88)	5.73 (2.86)	5.45 (2.91)	4.29 (2.14)	8.49 (4.52)	6.68 (3.33)	133.5	85.8
1992	7.73 (4.39)	5.98 (3.02)	5.58 (3.17)	4.32 (2.18)	8.50 (4.83)	6.57 (3.33)	138.5	90.9
1993	8.02 (4.56)	6.34 (3.31)	5.70 (3.24)	4.50 (2.35)	8.57 (4.87)	6.77 (3.54)	140.7	93.6
1994	8.54 (5.46)	6.63 (3.29)	5.93 (3.79)	4.60 (2.28)	8.81 (5.63)	6.83 (3.39)	144.1	97.0
1995	8.84 (5.23)	7.08 (3.62)	5.93 (3.51)	4.75 (2.43)	8.84 (5.23)	7.08 (3.62)	149.1	100.0
1996	9.41 (7.79)	7.42 (3.83)	6.16 (5.10)	4.86 (2.51)	9.08 (7.52)	7.17 (3.69)	152.7	103.6
1997	9.48 (5.33)	7.81 (5.30)	6.02 (3.38)	4.96 (3.36)	8.78 (4.93)	7.23 (4.91)	157.5	108
1998	9.87 (5.14)	7.98 (3.75)	6.06 (3.16)	4.90 (2.30)	8.69 (4.53)	7.03 (3.30)	162.9	113.5
1999	11.50 (6.38)	7.48 (3.07)	6.95 (3.86)	4.52 (1.86)	9.67 (5.36)	6.29 (2.58)	165.4	119

Notes: Average hourly wage rates in nominal and real values. Standard deviation reported into brackets. RPI, retail price index. AEI, average earnings index. RPI, base year 1987. AEI, base year 1995.

Construction of Employer-Tenure variable

The tenure variable I want to construct refers to the employer tenure; i.e. the amount of time individuals had spent with their current employer until the date they were interviewed. The variable is measured in months[20] and is constructed only for the individuals who were employed during the time of interview.

The construction of the employment variable is based on three main records, the wave-on-wave job history record *WJOBHIST*[21], the *Wave 3* lifetime employer history record *CLIFEJOB* and the *Wave 2* lifetime employment status history record *BLIFEMST*. The *WJOBHIST* record contains information on the employment history over the period between the 1st September of the year before the individual was interviewed and the date of interview of each wave, e.g. for *Wave 3*, *CJOBHIST* covers the period from 1st September 1992 to the date of *Wave 3* interview. These records exist only for individuals whose current labour force began sometime during the period that these records cover, e.g. *CJOBHIST* contains information on individuals whose current labour force status in *Wave 3* began at or after 1st September 1992.

The *CLIFEJOB* contains information on employer spells with start and end dates for the individual's employment prior to 1st September 1990, i.e. employer tenure start dates prior to when *AJOBHIST* record begins. The record is restricted to respondents that were interviewed at *Wave 2* and had another (full-time or part-time) paid job

20 Throughout the empirical analysis of the thesis though, employer tenure variable is transformed and measured in decades.

21 The first letter (W) in the name of the job history record refers to the particular wave. Therefore, for the *Wave 2* the name of the record would be *BJOBHIST* and similarly for the other waves.

(with different employer than the one in their previous employment spell) at *Wave 3*, that lasted more than one month.

The *BLIFEMST* record contains information about employment status spells, rather than changes in employers, covering the period since the respondent first left full-time education. The data collection was unrestricted, so all respondents at *Wave 2* were asked questions concerning their lifetime employment activities. This record can provide useful information about the employer start date spell but only when the previous employment status was "*not-employed*" and the recorded start dates (month and year) from the *BLIFEMST* record match exactly with the beginning of the current position at each wave.

The methodology followed for the construction of the employer-tenure variable is quite similar for all the waves. However, there is an additional step included to the succeeding *Wave 1* remaining BHPS waves. For illustration reasons, I will focus on the description of the tenure variable in *Waves 1* and *2*, for the rest of the BHPS waves the process is exactly the same with the one followed for the second wave.

One thing should be underlined before continuing on the description of the methodology employed. A main issue of concern in the construction of the employer-tenure is the identification of the beginning of the employment spell with a particular employer. The beginning of an employment spell does not necessarily coincide with the beginning of an employment spell with a particular employer. The respondent may have changed jobs but she may be still working for the same employer. Therefore, in order to identify the beginning of an employment spell with a particular employer, the respondent should either not be working previously (*unemployed*, *out of the labour market* or *student*) or specifically state that she works with a different employer than her previous one.

Starting now with *Wave 1*, the construction of employer-tenure is based on five steps, in every step the sample contains only individuals whose tenure variable has not been constructed in one of the previous steps. The first step is based on the *AJOBHIST* record. The individuals of concern are:

(a) Those who were either self-employed or employed with a different employer (*AJHSTAT*=2) in the most recent spell (*AJSPNO*=1) (spell closest to the date of *Wave 1* interview) and were not working with the same employer (*AJHSTAT*≠1) in the previous spell (*AJSPNO*=2). Or,

(b) Those who were employed with the same employer (*AJHSTAT*=1) at the most recent spell (*AJSPNO*=1) but were employed with a different employer or self-employed (*AJHSTAT*=2) in the exact previous spell (*AJSPNO*=2), so that we can identify the beginning of the employment spell with the current employer. In the case the individual was working for the same employer at the last two most recent spells (*AJSPNO*=1 or 2) then I check whether she was working at a different employer or was self-employed during the spell before these two.

Employer-tenure is defined as the period between the beginning of the employment spell (*AJHENDM*, *AJHENDY*) at the most recent spell (*AJSPNO*=1) or the exact previous one (*AJSPNO*=2) and the date *Wave 1* interview took place (*ADOIM*), for the two groups of individuals described above, respectively.

The second step is based on the *WINDRESP* records of the rest of the BHPS waves (*Waves 2-8*). Starting with the *BINDRESP* record, the analysis is focused on the individuals whose current employment status in *Wave 2* (*BJBBGM*, *BJBBGY*) started before or exactly when current economic activity reported in *Wave 1* (wave under examination) started (*AJBBGM*, *AJBBGY*). For those individuals employer-tenure is calculated as the period between the beginning of the current economic activity in *Wave 2* (*BJBBGM*, *BJBBGY*) and the date of the *Wave 1* interview. The process described above is repeated using alternatively the rest of the *WINDRESP* records.

For the next step, the *BLIFEMST* record is used. The individuals of interest here are those, whose start of employment spell (*BLESHM*, *BLESHY*) matches exactly with the date current employment began in *Wave 1*. In addition the respondents should be either full-time or part-time employed (*BLESHST*=2 or 3) at the spell of interest and not full-time or part-time employed in the exactly previous spell (*BLESHNO*), so that I can identify the beginning of the employment spell with the current employer. The employer-tenure is estimated as the period between the beginning of current employment in *Wave 1* and the date of *Wave 1* interview.

In the forth step, there are three alternative methods used respectively. The relevant information used, in all methods described below, for the calculation of the employer-tenure is taken from the *CLIFEJOB* record. Starting with the first method, the analysis focuses on the individuals whose employment spell, as reported in *CLIFEJOB* (*CLJBGM*, *CLJBGY*) record, started exactly when current employment in *Wave 1* started. In the case where seasons instead of months are stated in the date employment began, the individuals are excluded from this method. Employer-tenure here is simply the period over the beginning of the employment spell of interest from the *CLIFEJOB* record and the date of *Wave 1* interview.

In the second method employed, I relax the criteria. Here I am looking for individuals whose current employment spell in *Wave 1* started sometime between two consecutive employment spells as reported in the *CLIFEJOB* record (*CLJBBM*, *CLJBBY*, *CLJLFTM*, *CLJLFTY*). In addition when seasons are stated, they are replaced with months[22]. For those individuals, employer-tenure is constructed by calculating the months between the beginning of their current employment status and the date of *Wave 1* interview.

Finally in the third method used, the criteria are relaxed even more. Here the criterion for the selection of the individuals of interest is that the date of *Wave 1* interview must fall between the beginning and the end of an employment spell in the *CLIFEJOB* record (*CLJBBM*, *CLJBBY*, *CLJLFTM*, *CLJLFTY*). As before, seasons are proxied with months. The acquired tenure then is considered to be the period over the beginning of the employment spell of interest from the *CLIFEJOB* record and the date the individual was interviewed in *Wave 1*.

In the last step, followed for the construction of the obtained employer-tenure I look whether the current employment status reported in the succeeding waves began before the date *Wave 1* interview took place. More particularly, starting with *Wave 2* I look for individuals whose employment status in *Wave 2* (*BJBBGM*, *BJBBGY*) started before the *Wave 1* date of interview and who were either full-time or part-time employed in both *Waves 1* and *2* (*AJBSTAT* and *BJBSTAT*=2). Employer-tenure is defined as the period between the beginning of the *Wave 2* current employment status and the date of *Wave 1* interview (*ADOIM*). The same process is repeated for the other remaining waves.

The methodology described above is used in order to construct the employer-tenure variable for *Wave 1*. For the remaining waves the process is quite similar, with the addition of one step at the beginning. More specifically, initially I examine whether

[22] '*Winter*' is replaced with January, '*Spring*' with April, '*Summer*' with July and '*Autumn*' with October.

the current employment status of the wave of interest began before or during the date the interview of the previous wave took place. For example, when constructing the tenure variable for *Wave 2*, I check whether the current employment status began before or during the *Wave 1* interview took place. If this is the case, in other words if the individual continues to work for the same employer as in the previous wave (*Wave 1*), then tenure is simply constructed by estimating the period between the *Wave 1* and *Wave 2* date of interview and adding that to the employer tenure of the previous wave (*Wave 1*). After this step, the methodology followed is exactly the same as the one described above for *Wave 1*.

Construction of Actual Labour Market Experience

A distinction has to be made between the potential and the actual labour market experience. Usually, in the absence of the appropriate variables, researchers used to proxy labour market experience with the potential labour market experience, which is defined as the length of time in the labour market, constructed as the difference between the current age of the individual and the age when left full-time education (first or last time). This variable can sometimes be quite a satisfactory proxy of the actual labour market experience. However, BHPS includes detailed data that makes the construction of actual labour market experience feasible. Therefore, for the purpose of my analysis, I construct a variable that corresponds to the actual labour market experience an individual had obtained up to the time she was interviewed, for each of the first eight BHPS waves.

Employment periods are separated into full-time and part-time, according to the hours an individual normally works per week, while non-employment spells are categorised into spells of full-time education, unemployment or out of the labour market. More specifically, an individual is considered to work as a full-time employee, if she normally works at least 30 hours per week, otherwise she is characterised as a part-time employee (less than 30 hours per week). In addition, a respondent of the BHPS questionnaire is considered to be out of the labour market if she is retired, on maternity leave, long-time sick/disable, under family care, in a government training scheme or in a national/war service.

For the construction of the actual experience I start with ***Wave 2***, because in that year a lifetime labour market experience survey was conducted (*BLIFEMST* record). This record contains information about the labour market experience since first leaving full-time education, on all the individuals who had left full-time education at the time of the *Wave 2* interview. Therefore the second wave of the BHPS is the basis for generating the actual labour market experience for the rest of the waves. Consequently actual experience variable is available only for individuals that had left full-time education at the time *Wave 2* survey was conducted. Below there is a description of the three main steps followed in order to construct the actual labour market experience. In all the steps described below, when seasons are reported instead of months they are proxied with months in the same way as I do for the construction of the employer-tenure variable.

The first step is focused on the construction of the experience variable in *Wave 2*, based on the *BLIFEMST* record. The main variables used from that record were the *BLESLEN* (length of employment history spell) in order to identify the employment spells and the *BLESHST* (lifetime employment history status) to characterise them. First, individuals with missing information on these two variables are dropped from the sample. Then I simply summed up the spells by category (e.g. full-time employed) for each individual separately. This way I constructed a variable in *Wave 2* that corresponds to the actual experience an individual has obtained up to the date she was interviewed for *Wave 2*.

In the second step, I return to the first wave of the BHPS and construct the experience variable for that wave. The basic idea behind the process followed here is first to identify the employment spells during the period between *Wave 1* and *2* interviews. Then, by subtracting these spells from the *Wave 2* actual experience variable I can estimate the actual labour market experience of the individuals in *Wave 1*. Records *BLIFEMST*, *AINDRESP* and *BINDRESP* were used for the construction of the experience variable in the first wave. In particular, information on the lifetime employment history spells (*BLESHEM*, *BLESHEY*, *BLESHSM*, *BLESHSY*, *BLESHST*, *BLESHNO*, *BLESLEN*) and the dates of the *Wave 1* and *2* interviews (*ADOIM*, *BDOIM*, *BDOIY*) are acquired for that purpose.

The first stage in the construction of the actual experience variable is to identify the employment spells. The analysis is focused only on spells of changes in employment status that occurred during or after the *Wave 1* interview. Then I characterise the spells according to the employment status and add the spells duration by category for each individual separately, in order to get the difference between the *Wave 1* and *2* labour market experience. Finally, I subtract the estimated experience spells from the actual experience of *Wave 2* to get the *Wave 1* experience variable. For example, if an individual has started working before or during the *Wave 1* interview and has not stopped till the date of *Wave 2* interview, then we can easily calculate the employment spell by estimating the period between the two interviews. Then by subtracting the duration of this employment spell from the labour market experience of the individual at *Wave 2*, we obtain an estimate of her actual experience in *Wave 1*. Lets assume now a more complicated case where an individual starts working before *Wave 1* interview, stops after a few months, and starts working again before the *Wave 2* interview, having spent some months in unemployment. Here, there are three spells observed, the one covering the period between the *Wave 1* interview and the date when she stopped working, the second between the end of the first employment spell and the beginning of the second one where she was unemployed and the last one between the beginning of the second employment spell and the date of the *Wave 2* interview. In that case, we should sum up the first and the third employment spell and subtract them from the *Wave 2* actual experience variable in order to get an estimate of the *Wave 1* experience variable.

The actual labour market experience of the remaining six waves is constructed in the third step. The methodology followed is the same for each wave, therefore for illustration reasons I will focus on the process of construction the experience variable for *Wave 3*. The sample is divided into three sub-samples:

(a) The individuals from record *CJOBHIST* whose last change in labour status began before the *Wave 2* interview. More specifically the first sub-sample includes those individuals whose most recent change in labour status started on September 1992 or before (*CJHA9LY*=1), or whose last employment spell started after September 1992 (*CJHA9LY*=2) but before the date of *Wave 2* interview.

(b) The individuals from record *CJOBHIST* whose last change in labour status began at the time of the *Wave 2* interview or afterwards. In particular individuals whose most recent employment spell started after September 1992 (*CJHA9LY*=2) and after the year of *Wave 2* interview, or whose last change in labour status occurred after September 1992 (*CJHA9LY*=2) and after or during the date of *Wave 2* interview.

(c) The remaining of the individuals from *CINDRESP* record.

For all the groups of individuals the main steps in the construction of the experience variables can be summarised in the following. First, keep individuals of interest. Then identify the employment spells and characterise them. Sum up the spells by category for each individual. Finally, add them to the experience variables of the previous wave, in our case *Wave 2*, to get the experience at the date of interview of the current wave.

For the first group of individuals the construction of employment spells is based on the dates labour force spells ended (*CJHENDY*, *CJHENDM*) and the dates of *Wave 2* and *3* interview. Spells can be either the period between the *Wave 2* interview and the end of labour status (*spell 1*), or the period between the end of labour status and *Wave 3* interview, or *Wave 2* interview and *Wave 3* interview (*spell 2*). The characterisation of *spell 1* is based on information from *CJIBHIST* record (*CJHSTAT*, *CJHSEMP*). If the individuals have responded that they were in different job but with the same employer (*CJHSTAT*=1) characterisation is based on the *BINDRESP* record (*BJBSTAT*, *BJBHRS*). Similarly, for *spell 2* the identification is based on information from *CINDRESP* record (*CJBSTAT*, *CJBHRS*).

Continuing with the second sub-sample of individuals, the construction of employment spells is based on the dates employment spell began and ended and on the dates of *Wave 2* and *3* interview. The constructed spells are divided into three types:

(a) Those covering the period between *Wave 2* interview and the end of a labour force spell, for the least recent spell (*spell 1*).

(b) Those for the period between the end of a labour force spell and *Wave 3* interview, for the most recent spell (*spell 2*). And finally,

(c) Those covering the period between the beginning and end of a labour force spell, for all the spells between the least and the most recent one (*spell 3*).

The characterisation of *spell 1* is based on information from the *BINDRESP* record (*BJBSTAT*, *BJBHRS*), while labour force spells belonging in *spell 2* are characterised based on *CINDRESP* record. *Spell 3* similarly is categorised using information from the *CJIBHIST* record (*CJHSTAT*, *CJHSEMP*). If individuals had responded that they are in a different job but with the same employer (*CJHSTAT*=1) then the identification is made using the information from the exactly previous spell from the one referred. Individuals whose labour status cannot be identified are excluded from the sample.

Finally, the third group contains the remaining of the individuals. The spells constructed are simply the period between the ***Wave 2*** and ***3*** interviews, and their characterisation is made using information from the ***CINDRESP*** record.

The process described above is repeated for the rest of the BHPS waves in order to construct the actual labour market experience variable.

Chapter 3

3 Profitable Career Paths: The Importance of Occupational and Industry Expertise

3.1 Introduction

In the previous chapter I provide a thorough examination on the importance of employer tenure on individuals' earnings profiles. The findings from the analysis presented suggest a modest but positive tenure effect on wage growth for both male and female employees. The most popular and probably widely accepted theory that explains this observed relationship is the human capital theory that goes back to the pioneering work of Becker and Mincer in the 60's and 70's. The cornerstone of human capital theory is that individuals over the years acquire a variety of skills in work that are quite valuable to their employers due to their firm/job-specificity. Almost universally, all studies on the tenure-wage effect distinguish a worker's working experience into two components, general labour market experience and employer tenure. Within the human capital framework, the effect of the former refers to return to general labour market skills, while the effect of the latter is interpreted as the reward for employer-specific skills. In this chapter, I challenge this assumption and explore whether the typical worker's human capital stock should be further disaggregated. Particularly, I examine the existence of industry and occupation-specific skills.

Studies on displaced workers have revealed that industry may be an important dimension across which skills are transferable. Although most displaced workers suffer wage losses, workers who switch industries following displacement usually suffer greater losses than observationally similar workers who find jobs in their pre-displacement industry (Podgursky and Swaim 1987; Addison and Portugal 1989 a, b; Kletzer 1991; Ong and Mar 1992; Carrington 1993; Ong and Lawrence 1993; Neal 1995). If the accumulated skills in work are mainly industry-specific rather than firm-specific, then it is expected that employer-tenure will have only a modest effect on wages. Furthermore, the observed wage losses of the displaced workers will be more severe for those who find employment in another industry, since they will forego their previously accumulated industry-specific skills. According to Neal, "*the difference between switchers and stayers is that switchers forfeit compensation for their industry-specific skills*" (pp. 657). The author acknowledges the fact that a portion of industry-specific compensation reflects labour market rents. Nevertheless, there are still important wage profile differences between stayers and switchers due to the fact that the latter forfeit, in the post-displacement job, compensation for their already obtained industry-specific skills. Furthermore, the author argues that, after all, firm-specific factors may contribute little to the observed slope of the wage tenure profile.

Parent in a recent study (2000), based on a standard wage equation model, establishes that the returns to seniority are very small or they do not exist at all. From the author's point of view, what is important for the wage profile in terms of human capital is industry specificity rather than employer specificity. According to his findings, it appears that past studies have overlooked an important factor in analysing the effect of tenure on wages. Industry-specific skills are found to play a far more significant role in the wage growth process than employer-specificity.

The question addressed here is whether the accumulated in-work human capital should be further decomposed, apart from the employer-specific and the general labour market components. A possible candidate, as already outlined above, is industry-specific skills. A worker through the years may acquire some skills that are appreciated and rewarded not solely by the current employer, but by other employers as well in the same industry. If that proves to be true, then that implies that industry-specificity does exist and furthermore it has a significant role in the wage determination process. In this framework, an individual working in the manufacturing sector, for example, could obtain some skills that will be equally appreciated by other employers in that industry. Therefore, it would be expected that her experience in the manufacturing industry should have a positive effect on her wages in any future employment in the same industry. On the other hand, if she moves to another industry, then she would forfeit these industry-specific human capital wage premia.

One may argue though that it is occupational experience that matters instead of industry experience. Let's consider again the example of the worker that is employed in the manufacturing sector, as a secretary. In the case of industry-specificity of human capital, these accumulated skills, specific to the manufacturing industry, should not have any effect on her wages if she switches industries, for instance if she is employed in the banking sector, as a secretary again. However, one might wonder what sort of skills a secretary could obtain in the manufacturing industry, that are specific to this particular industry. Probably, it would be more reasonable to assume that it is occupational-specificity of human capital that should be examined. A secretary would most likely acquire skills that are specific to her current occupation, therefore transferable among different employers and industries, as long as she is working as a secretary. In the case that an individual changes occupations, then it should be expected that she would forfeit these wage premia associated to her expertise in her previous occupation.

Individuals are not equally well equipped to enter each occupation, and they self-select on the basis of their comparative advantage for the occupation. The occupational choice process can be described as a utility maximisation problem. If we assume that occupational choice determines, on average, subsequent earnings growth, then each individual acts as a far-sighted optimiser. This economic agent early in her adult life chooses her career path[23], in other words, chooses the occupation which best achieves her lifetime objectives that are represented both by her lifetime income stream and tastes for specific occupations. The parameters that determine the self-selection of workers into occupations can be distinguished into two main groups. On the one hand, there are the personal tastes and motivation, allied to family background, of the individual. In general, socio-economic variables play an important role in occupational choice (Robertson and Symons, 1990), since, in a way, they form the future expectations of the individual and her taste and preferences towards life-style, priorities and quality in life. One the other hand, ability and the attributes of the individual are important determinants of the choice of occupation. Each worker is endowed with a level of ability for each sector, so they will sort themselves into occupations according to their comparative advantage (Roy, 1951). Since individuals aim to maximise their utility, they tend to choose occupations that cater their personal strengths.

A worker consists of a bundle of characteristics that are embodied within the person and sold on the market as a package deal. The way these characteristics are utilised and valued will differ across occupations, since technology, among other parameters, varies across occupations. Technology plays a central role in determining the weights that are placed on various personal characteristics and consequently different technologies might require the use of different characteristics or at least emphasise them differently. Thus each individual, knowing her ability, forms an estimate of her expected earnings in each occupation and, taking into

[23] Despite the fact that there is both upward and downward movement, the position of individuals in the occupational hierarchy is highly stable over time (Nickell, 1982).

account her particular taste for each occupation, chooses the one which offers the greatest utility. One would probably expect then that the expertise the individual acquires over the years in this, best chosen to match her ability, occupation would play a significant role in her earnings profile.

The first paper, to my knowledge, that directly examines the significance of occupational investment, as part of the post-school human capital, in wage determination is a study by Shaw (1984). Shaw in her paper argues that occupational investment, which is the accumulation of skills an individual acquires to perform work within a particular occupation, is a strong determinant of earnings and far superior to general labour market experience. Total occupational investment in a particular occupation is calculated as the weighted sum of the individual's accumulated quantities of occupation-specific investment, based on the hypotheses that some portion of the occupational skills are transferable across the various occupations and that occupations are characterised by different degrees of general investment. According to the author, although total labour market experience and occupational investment are both proxies of the individual's stock of general human capital, the latter is a far better measure. The reason is that occupational investment can be considered as a heterogeneous measure of general labour market skills. Therefore, the introduction of occupational investment, which replaces the homogeneous measure of years of experience in the labour market (total labour market experience), reduces the otherwise unobservable heterogeneity in the individual's general post-school investment. The main empirical framework of this study is based on a standard Mincer wage equation model, where the author introduces occupational investment in place of total labour market experience. The findings from these wage equations strongly suggest that occupational investment has a very important contribution on individual's earnings profiles, "*empirically* *dominating the standard experience variable as a proxy for the stock of general human capital investment embodied in the individual*" (pp. 338).

In the analysis that follows, I examine whether individuals' accumulated human capital in work has an industry and/or occupational-specific dimension and the significance of these kind of skills in the wage determination process. The findings of this study can be of significant importance to the better understanding of wage growth and may be rather enlightening on issues related to career choices. In addition, identifying the type of specilisation and expertise that is central to a worker's future prospects can also be informative and helpful to policy makers. Particularly to those who target unemployment, through training programs, and aim for flexibility in the labour market based on skilled and employable individuals. In *Section 3.2*, I explain the methodology employed for the purpose of the analysis, followed by a description of the data set used here, *Section 3.3*. The main findings are summarised in *Section 3.4*, with a discussion on their implications with respect to the evolution of an individual's earnings profile. The estimates on the wage equation models suggest the existence of occupational specific skills and the significance of individuals' expertise in their wage determination process. The evidence on the industry-specific human capital, on the other hand, is not so strong. Nevertheless, despite the uncertainty concerning the industry experience, even in the case where industry specificity matters, the estimated effect does not appear to be of great magnitude. In *Section 3.5* a more detailed examination is pursued. Here I explore whether these derived effects are uniform across the various occupations or industry sectors or not. Indeed, the findings suggest that there is heterogeneity in the returns to industry and occupational experience, suggesting that the previous estimates in *Section 3.4* are driven by particular occupational and industry choices. Finally in *Section 3.6*, I conclude the discussion highlighting the major findings and implications of this study.

3.2 Methodology

The framework adopted here, similar to the one Parent (2000) employs in his study, is based on a standard wage equation model. My working assumption is that employer-tenure, total industry and occupational experience are competing effects in the wage determination process. Initially, consider the following wage equation model

$$W_{ijt} = \alpha + \beta_1 T_{ijt} + \beta_2 E_{it} + \beta_n X_{ijt} + \varepsilon_{ijt} \tag{3.1}$$

for the individual i, with the j employer, the period t, where T_{ijt} represents the employer tenure, E_{ijt} is the total labour market experience and X_{ijt} is a $1 \times n$ control vector that does not include industry or occupational experience. If industry experience plays a significant role in the wage setting, then I would expect that the inclusion of this variable in the control vector, alongside employer tenure, would decrease the magnitude of tenure effect on wages. The reason is that the returns to tenure are most likely overestimated when industry experience is not controlled for in a wage equation model. A portion of this estimated tenure effect should be attributed to the industry-specific skills that an individual has obtained in work rather than to those skills that are only appreciated by the current employer. In like manner, if it is occupational experience that matters, then its inclusion in the covariates should have a similar negative impact on the magnitude of the estimated returns to employer-specific skills.

The main framework of my analysis has already been outlined in the paragraph above. In order to address the issue of industry-specific and occupational-specific human capital, I investigate whether employer tenure effect decreases when they are alternatively controlled for in the estimated model. Initially, I consider a wage equation model without including a variable for either industry experience or, occupational experience. The wage equation model is then re-estimated adding alternatively industry and occupational experience and both. Any observed significant decrease in the magnitude of tenure effect in these models may provide us with the insight on how total working experience should be decomposed and have important implications on the evolution of life cycle earnings and on job mobility issues.

Consider now a wage equation model

$$W_{ijkht} = \alpha + \beta_1 T_{ijt} + \beta_2 E_{it} + \beta_3 Ind_{ikt} + \beta_4 Occ_{iht} + \beta_n X_{ijkht} + \varepsilon_{ijkht} \quad (3.2)$$

where W_{ijkht} represents the log hourly wage of individual *i*, with the *j* employer, having the *h* occupation in the *k* industry, the *t* period, and industry experience Ind_{ijkht} and occupational experience Occ_{ijkht} are included in the regressors alongside employer tenure T_{ijt} and total labour market experience E_{ijt}. One issue of concern related to the estimation process is the fact that the obtained coefficients of interest $(\beta_1, \beta_2, \beta_3$ and $\beta_4)$, based on OLS, are likely to be biased due to potential correlation between these variables and unobserved individual and job/sector match effects. In particular, the error term ε_{ijkht} can be decomposed into five components,

$$\varepsilon_{ijkht} = \alpha_i + \vartheta_{ij} + \gamma_{ik} + \omega_{ih} + \eta_{ijkht} \quad (3.3)$$

where unobserved heterogeneity is analysed into an individual effect (α_i), a job-match effect (ϑ_{ij}) ,an industry-match effect (γ_{ik}) and an occupation-match effect (ω_{ih}). The individual effect (α_i) represents the individual's unobserved ability, while the job-match effect (ϑ_{ij}) captures the quality of the employment relationship stemming from search activity. The inclusion of industry experience variable in the wage equation adds an extra source of unobserved heterogeneity. That is the unobserved industry-match effect (γ_{ik}), that represents the unobserved quality of the match between the individual and the industry where she works in (Parent, 2000). Furthermore the self-selection of workers into occupations means that there is an additional source of endogeneity bias driven by unobserved quality match between the individual and her current occupation (ω_{ih}). Therefore, in total there are four sources of potential endogeneity bias in the wage equation model, given by equation (3.2). Individuals with high unobserved ability (high α_i) most likely experience lengthy and less interrupted employment spells, while better matches, choices of job and industry (high ϑ_{ij} and γ_{ik}) are more likely to occur to individuals with more experience, as the result of human capital and lengthy search. In addition, individuals with high unobserved ability are likely to choose well paid and prestigious occupations (high ω_{ih}).

The analysis is carried out based on OLS, generalised least squares (GLS) and within-group fixed-effect (FE) estimators. For the panel estimators, two alternative observation units are considered in the estimation process. Initially, I use the individual as an observation unit and then the individual working for a particular employer. In the latter case, when a respondent in my sample is observed working for different employers, she is treated as a different individual. The idea behind this is that potential endogeneity bias in employer tenure estimates, driven by unobserved job-match effects, may be more effectively controlled when I consider in the estimation process that the employer-employee match has some '*unique features*'.

3.3 Data Description

The empirical analysis is carried out using the unbalanced panel sample of male and female full-time employees (BHPS, waves 1-8) from *Chapter 1*. The sample sizes though are reduced, since in some cases there is missing information on industry and occupational experience, the two new variables I use in this chapter. Some summary statistics of this sample are provided in *Table A.3.1*.

The panel sample consists of 985 male and 734 female workers that give a total of 5027 and 3587 observations, respectively. Male respondents appear to spend on average seven years and a half with a particular employer, while their female peers report staying one year less on average. Furthermore, male employees overall accumulate more industry experience than female workers do, however both of them report on average similar years of occupational experience. These observed patterns in the accumulation rate of various kinds of working experiences between male and female employees should probably be attributed though to the fact that female individuals tend to take more time off the labour market than their male colleagues do. As we can see from the table, although potential labour market experience is at similar levels for both of them, actual labour market experience based on true employment spells suggests that it is the male respondents that have the longest job-market history. In addition, despite what industry and occupational experience imply, male workers change occupations and industry sectors where employed slightly more frequently than female employees. One thing that may raise some concern is that both male and female respondents sometime report that they are changing industry or occupation, while they remain with the same employer. From *Table A.3.1* we can see that the number of industry and occupation changes exceeds the total number of employer changes, the sample was employed by. Whether these reported movements are true mobility patterns or just misclassification errors is an issue of concern. However the answer is not an obvious one.

For the purpose of the analysis the construction of two new variables, the industry and the occupational experience, is required The former refers to the years an individual has been working in a particular industry and can be thought as a proxy of the industry-specific human capital accumulated in work. Similarly, the latter, measures the years a worker has spent in a certain occupation, which corresponds to the individual's occupation-specific skills acquired over these years. The variables are constructed, alternatively, both on the 1-digit and 2-digit level of industry and occupation classification and only employment spells where the respondent reported working for an employer (not self-employed), either part-time or full time, are taken into consideration. A question that may arise is which of these measurements is the more appropriate one. Is it sufficient to measure occupational experience, for example, at the broader 1-digit level of classification or should we focus on a more detailed level? The answer to this question partly has to do with the homogeneity of occupational skills. If acquired skills within the broader 1-digit level of occupational classification are quite homogeneous then it is probably adequate to measure experience at that level. In the alternative case, where skills are significantly heterogeneous, probably one should focus on a more detailed level of classification. Leaving though aside the question regarding the homogeneity of skills, there is another argument as well. Sometimes the changes in occupation, for example, that we observe at the 2-digit level of occupational classification may be just movements within the broader 1-digit level that represent a career progression. In that case probably it would make more sense to ignore movements that occur at the 2-digit level and focus on a broader level. Although I am more inclined in using industry and occupational experience measured at the 1-digit level of classification, for completeness reasons in the analysis that follows I employ both measures/levels.

A further distinction has to be made between two alternative ways of measuring these variables. They can be measured based on either continuous spells, or not necessarily continuous spells. In the first case, industry experience, for example, is measured by the consecutive years an individual has been working in the same industry. While, in the latter case, industry experience is measured by the years a worker has been in the same industry in total, not necessarily consecutive. In order to make this distinction clear, consider the case of a worker who has spent a few years with an employer and then has been employed in a different job in an industry, different than the previous one, that she has been working sometime in the past. Now, if I measure industry experience based on the continuous spells then when the worker changes jobs, her industry experience should reset to zero. However, when I measure it based on the second method, industry experience should not reset to zero but to the number of years she has spent in that industry in the past. The difference between these two ways of measuring industry experience can be thought of as reflecting different rates of depreciation of the industry-specific human capital. If one thinks that industry-specific skills depreciate rapidly, then it might be better to use continuous spells. Yet, another point that I should mention is that the industry experience variable based on not necessarily continuous spells most likely does not eliminate much of the variance in employer tenure that is important in the identification of the tenure effect. Since I do not have any information on the rate at which industry-specific human capital depreciates, I am in favour of the latter method for their desirable feature in the estimation process of tenure effect. A similar argument can be raised for occupational experience, therefore all the estimates presented below are based on spells of industry and occupational experience that do not have to be necessarily continuous. In the Appendix at the end of this chapter, I provide a quite detailed description on the construction of these two new variables that should enable the reader to re-produce them.

3.4 The Role of Industry and Occupational Specificity

The aim of my analysis is to examine whether part of the estimated employer-tenure effect on wages should actually be attributed to industry-specific or occupation-specific human capital or both. In order to explore that I estimate a wage equation model where initial only employer-tenure, alongside potential total labour market experience and other regressors, is included. Then, this earnings equation is re-examined, this time with the inclusion of industry experience or/and occupational experience. The attention is focused on the estimated coefficients of the variables of interest. Any significant change in the derived effects across these models, could be quite informative on how transferable are skills acquired in work and on their wage premia.

The estimates are based on a standard Mincer (1974) wage equation model, where the dependent variable is the log of hourly wage rate. The control vector on the right-hand side of the equation includes a quadratic in potential labour market experience, a cubic in employer-tenure, industry and occupational experience and controls for the characteristics of the individual and of the workplace where employed[24]. The analysis is carried out separately for male and female employees and the findings are summarised in ***Tables 3.1*** and ***3.2*** below. In each table, the estimated effect of ten years of employer-tenure (*T10*), industry experience (*Ind10*), occupational experience (*Occ10*) and total labour market experience (*PotExp10*) are presented, a fairly standard way in the literature to present the estimates. The

[24] The Appendix gives a list of the regressors included in the wage equation model.

first column in each table refers to the wage equation model where employer-tenure and total labour market experience are included (from the four candidate variables/proxies of the labour market skills). In the second and fourth column 1-digit industry and occupational experience are included, respectively and also in the third and fifth, but at a 2-digit level this time. Finally, the last two columns show estimates when both industry and occupational experience, alongside employer-tenure and total labour market experience, are considered.

Starting the analysis with the sample of male-employees, OLS estimates are summarised in the first part of ***Table 3.1***. As we can see from the first column, the returns to ten years of employer-tenure, when industry and occupational experience are not controlled for, are around 8.5 per cent. General labour market skills in this case are estimated to have a contribution of 24.4 per cent. When industry experience is included in the wage equation (second column), the tenure effect is slightly reduced while industry-specific skills appear to explain only a small part of the variation in wages (3.5 per cent ten-year effect). The impact is stronger when 2-digit level industry experience is used; tenure effect is further reduced while industry-experience has a 5 per cent effect. The inclusion of occupational experience in the regressors restricts the contribution of employer-tenure around 6 per cent. Conversely, occupation-specific human capital appears to matter more in the wage determination process, with the effect varying between 8 and 10 per cent depending the level of occupational classification. The picture remains the same in the last two columns, where both industry and occupational experience are included in the covariates. Occupation-specific skills have a similar effect on wages, while employer tenure appears to contribute even less than before. Interestingly enough, industry experience does not seem to have a significant role anymore. The fact that the effect of industry-experience is increased, while in the case of occupation is reduced, when 2-digit level of classification is used can probably be explained by the different rates of industry and occupational mobility in the male sample. As we can see from *Table A.3.1*, male workers tend to change more frequently occupations than industries[25]. Finally, the returns to total labour market experience are slightly reduced when either industry or occupational experience or both are included in the estimated model, nevertheless the ten-year effect in all cases is around 20 per cent. The first impression one gets from these estimates is that occupation-specific human capital may have a significant contribution on an individual's earnings profile. On the contrary, the evidence is not so supportive to industry experience.

One should acknowledge that the estimates based on OLS may suffer from potential endogeneity bias, driven by unobserved individual characteristics and job and/or sector match effects. Therefore, the wage equation model is re-estimated using panel estimators[26], and the findings are summarised in the rest of the table. Although the Hausman test performed (not included here) is profoundly in favour of the fixed effect estimator, for completeness reasons I present here estimates based on both fixed effect and random effect model. The picture remains fairly similar to the one discussed above, however there are some slight differences depending on the choice of estimator. The addition of industry experience in the regressors vector has an effect similar to the one suggested by OLS (columns 2 and 3). Although employer-tenure effect reduces it still remains larger than the industry experience

---

[25] Whether this observed difference in the patterns of mobility is actually true or not, is unknown to the author.

[26] Parent (2000) argues that residuals are likely to be serially correlated due to the presence of a fixed individual effect, driven by the fact that individuals are observed over a number of years. The author for that reason employed feasible random-effects, allowing for AR(1). However the findings appear to be quite similar to those based on random-effects. Therefore estimates are not presented here.

effect, with the only exception the case where fixed-effect estimators are employed and the observation unit is an individual working for a particular employer. Furthermore, the contribution of industry-specific human capital increases in magnitude when a more detailed industry classification is used. Moving in the next two columns, we see that, in general, when panel estimators are employed the impact of occupational experience on wages is reduced, especially in the case of fixed-effects. Although the picture is not completely uniform, overall we can say that the effect of occupational experience appears to be more significant than, or in the worst case equal to, the effect of tenure. As before, the use of 2-digit classification in occupation reduces its estimated magnitude. Finally, when both industry and occupational experience are included, we observe no significant difference between OLS and random-effects in the '*ranking*' of the contribution of the human capital variables, although their size is altered to some extent. The only case where employer-tenure effect is more significant, in terms of magnitude, compared with occupational experience is when the fixed-effect estimator is employed and the observation unit is the individual. Considering that both potential labour market experience and the time trend included in the wage equation model increase by one unit (one year) from wave to wave, the identification of the linear term of potential experience and of the time trend is not feasible, when fixed-effect estimators are employed. Therefore, I exclude the linear term of potential experience from the estimated model and the obtained coefficient of the time trend now reflects their joint effect. Consequently, I do not report the ten-year effect of labour market experience, as I do with the other estimators (OLS and random-effects), since I cannot distinguish these two effects. Overall, the analysis presented above clearly suggests that occupation-specific human capital is wrongly overlooked in the literature so far. The estimated tenure-effect should probably be attributed to those skills that are specific to the worker's current occupation rather than to his employer. The evidence on industry specificity, although not so clear, is generally not very supportive to its existence. Even if industry-specific accumulated skills do exist, it is occupational experience and expertise that dominates the wage determination process.

Turning now my attention to the female sample of employees, *Table 3.2* presents the estimated effects of accumulated skills in work. Based on the OLS estimator, employer tenure appears to have an effect of 9 per cent (ten-year effect) that is reduced when either industry or occupational experience is included and becomes insignificant when both are considered in the estimated model. On the other hand, industry experience has an 8 per cent effect that reduces with the inclusion of occupational experience. The latter is estimated to have an effect of around 15 per cent (1-digit level) and 10 per cent (2-digit level) irrespective to whether industry experience is included or not in the wage equation model. Total labour market experience appears to have an effect of 15 per cent that falls notably when either industry or occupational experience or both are included in the wage equation. When the random-effect estimator is employed, with the individual used as an observation unit, we observe that, first of all, the magnitude of the estimated effects is reduced in all cases. Furthermore, at the 1-digit level, industry experience and employer-tenure appear to have a similar modest contribution on earnings. However, at the more detail level of classification, the former has an effect of around 5 per cent (ten-year effect) while the latter becomes insignificant. Occupational experience throughout the estimates, although reduced, seems to play a far more important role than the previous two with an effect of 6 to 7 per cent. When the individual-employer match is used as an observation unit, the estimates slightly change. Employer-tenure effect is noticeably increased and now it exceeds the industry-experience effect at the 1-digit level, and is similar to it at the 2-digit level. The picture does not change a lot for occupational experience, which still appears to have a significant role in the wage determination process. Finally, the estimates based on the fixed-effect estimator[27] appear to alter only when the observation unit considered is the individual-employer match. In this case, employer-tenure effect increases significantly[28] (above 10 per cent the returns to ten-year of tenure) and is estimated to have a more important role on wages, compared to industry and occupational experience. Overall, the estimates in ***Table 3.2*** highlight the existence of occupational-specific human capital and its significance in the wage determination process. On the other hand, the evidence on industry-experience is not conclusive, although there are some indications that it may have a modest effect on an individual's earnings.

A final comment concerning the returns to total labour market experience. The estimated effect appears throughout the estimates to be rather limited, however that is something that probably we should expect since the variable used is the potential labour market experience. As we can see in ***Table A.3.1***, there is a notable difference between potential and actual labour market experience. The former is 7 years lengthier than the latter, which is something quite common in the female population in general, because female workers take more time out of the labour market, mainly due to family reasons. I replicate the analysis this time using actual

27 Similar to the case of male employees, the fixed effect model appears to be more appropriate based on the performed Hausman test (not presented here), compare to a random effect model.

28 One thing that probably worthies mention here is that there is a considerable difference between male and female workers in what happens in the returns to tenure when the observation unit in the panel estimators changes. If the individual working for a particular employer is defined as a unit in the panel estimators, then we observed a reduction in the estimated employer-tenure effect in the case of male employees and an increase in the case of female workers. The fact that these two effects go to opposite direction probably suggests that there may be some sort of positive selection of male workers in high paid jobs and a negative one for the female workers. To put that in a more formal way, endogeneity bias in the returns to tenure driven by unobserved job-match effects appears to overestimate the effect of tenure for the male sample and underestimate it for the female employees.

(full-time) labour market experience[29] (not included here) and find that the estimated returns to total labour market experience seem to be more '*realistic*' than before. The effect appears to be below 20 per cent based on OLS estimators, around 20 per cent when the random-effect estimator is employed. The inclusion of actual instead of potential labour market experience does not have a dramatic impact on the magnitude of the other human capital variables of concern, despite the slight variation in the estimates. In the case of fixed-effect estimator, there is an identification issue related to actual labour market experience. Since both employer-tenure and actual labour market experience increase by the same amount between waves, the estimation process based on fixed-effects makes the distinction of the effect of the linear terms of these two variables impossible. Therefore, one of these terms is dropped out of the estimated wage equation model. This basically results in obtaining an estimate that represents the joint and indistinguishable effect of the linear terms of tenure and actual working experience. Hence, I cannot derive the ten-year effect of either employer-tenure or actual labour market experience.

Summarising the discussion in this section, we see that the analysis suggests that individuals accumulate in work skills that are specific to their occupations. This kind of transferable and competitive skills prove to be quite valuable in workers' earnings profiles, since employers appreciate and reward them accordingly. The evidence on industry specificity is not conclusive, but even if it exists, its effect is dominated by occupational expertise in a wage equation model.

[29] The estimates remain fairly similar when I include full-time and part-time employment spells in the calculation of actual labour market experience.

3.5 A Closer Examination on Occupational and Industry Experience Effects

The discussion in the previous section clearly indicates that occupational experience is an important determinant of an individual's earnings profile. The more experienced an individual is in a particular occupation, the higher her wages are going to be. In other words, the workers who, in a way, stay loyal to their '*career plan*' and seek and acquire specific knowledge and experience in their chosen occupation are likely to be more rewarded by their employers, ceteris paribus. One question though that the analysis above does not answer is whether this finding is uniform across the different occupations or not. We know that individuals choose their occupation based on their comparative advantage, i.e. choose a career that best suits and emphasises their strengths. Therefore, it is quite useful to know whether there is homogeneity in the accumulation rate and the returns to occupation-specific human capital across various occupations, or there are different patterns dictated by the nature of each occupation. One will probably expect the effect of occupational-experience to be rather high in those occupations that require and attract high-ability workers, and quite limited or insignificant in the not so demanding occupations. This is probably due to the '*anybody-can-do-it*' effect of the latter occupations (Roy, 1951), which says that if anyone is as good as anybody else to perform a particular task, then that occupation is more likely to be chosen by individuals of average or below average ability. In this section therefore, I explore whether there are significant differences in the way occupational-experience is rewarded across the various occupations. There are two obvious ways to pursuit this idea, either run separate regressions according for each occupation or include interaction terms between occupational-experience and occupational dummies in the wage equation model. I am in favour of the second approach since dividing the sample according to occupational choice would result to sub-samples of rather limited size that would probably make the estimation process difficult and more susceptible to sample selection biases. Therefore in the analysis that follows I re-estimate the wage-equation model where alongside the other regressors used above (summarised in *Table A.3.2*) I include interaction terms between occupational dummies[30] (1-digit *SOC* classification) and employer-tenure, potential labour market experience and occupational experience polynomials.

The findings on the male and female sample are summarised in *Tables 3.3* and *3.4*, respectively. Each column in these tables refers to a choice of different estimator (OLS, random-effects or fixed-effects) and each row represents the returns to ten years of experience of the human capital variables of interest. In addition a test is performed where I formally examine whether the observed variation in the estimated effect of a particular human capital variable across different occupations is statistically significant or not. Starting my discussion with the male sample (*Table 3.3*) we see that there is some fluctuation in the returns to ten-year of employer tenure depending on the occupation reported by the individual. Although tenure appears to have an insignificant effect in many occupations, there are a few cases where it actually has a noticeable effect on earnings. In particular, the findings suggest that seniority and employer-specific skills have a strong positive effect mainly in *clerical and secretarial* occupations and in *craft and related* occupations, with an estimated ten-year impact of above 10 per cent on average. However, the performed test implies that this variation in the returns to tenure is only significant when random-effect estimators are employed. Similarly, according to the test on the effect of ten-year of potential working experience, general labour market skills are equally rewarded across the various occupations, despite the derived fluctuation in the estimates. Industry experience, which is assumed not to vary over the different

[30] *Tables A.3.5* and *A.3.6* in the Appendix provide a detailed '*map*' on how male and female employees are distributed across the various occupations and industry sectors (1-digit level of classification) in my sample.

occupations (hence no interaction terms are used) is estimated to have only a modest positive effect on earnings that does not exceed the 4 per cent (ten-year effect). Finally, the findings on occupational experience are quite interesting and insightful. In the previous section I demonstrate that occupational specificity plays a rather important role in the wage determination process. Here the estimates suggest that the previous findings are actually driven by some particular occupations and are not uniform over the whole '*landscape*' of occupational choices. We see that there is a quite strong impact for those individuals who have *managerial*, *professional* or *associate professional* or *technical* occupations (*SOC*: 1,2,3). This is particularly true though for the *managers and administrators*. Acquiring a ten-year experience in this occupation (*SOC*: 1) appears to have an effect between 15 and 30 per cent (depending on the estimator used) and that on average is even higher than the effect of general labour market skills, traditionally considered as the human capital variable with the highest returns. *Managers and administrators* are far better off when they focus on developing their '*expertise*' rather than investing in any other kind of human capital. Furthermore, estimates on OLS and random-effects (II) imply that there are significant returns to *sales* associated occupational experience. It seems that the more experience an individual acquires as a *salesman*, the more persuasive that he is, hence the higher his earnings are going to be (assuming sales are directly related to his wage). Apart though from these occupations outlined above, there is no evidence to support something similar for the rest of the occupations, where their returns appear to be negligible. One final comment, the performed test verifies that these observed patterns between the various occupations are indeed significant, providing a further support to my discussion above.

The results in *Table 3.4* tell us a slightly different story for the female workers. Employer-tenure is uniformly estimated to have an insignificant effect on earnings over the various occupational choices. On the contrary, there appears to be a noticeable variation in the returns to potential labour market experience depending on the individuals' occupations, which is verified to be significant in the case of OLS and random-effects (II). According to these findings, general labour market skills are highly rewarded only in the prestigious *managerial and professional* occupations and in the, popular to female employees, *secretarial* occupations. In the rest of the occupations, potential working experience does not seem to have any significant impact on individuals' earnings growth[31]. Industry specificity as well appears to be unimportant, apart from the case of random-effects (II), in the wage determination process. Finally, the picture on occupational experience is not very clear. Although the findings suggest that there is some variation in the returns to occupational expertise, the performed tests imply that this is true only in the case of OLS and random-effects (I). Similar to the estimates on the male employees, occupational experience seems to be significant mainly in the case of the highly–esteemed *managerial*, *professional* and *technical* occupations (*SOC*: 1,2,3), where their ten-year effect is calculated to be around 15 per cent on average. Overall, the main conclusion that we can draw from ***Tables 3.3*** and ***3.4*** is that there is heterogeneity in the returns to occupational experience across the various occupational choices. The estimated impact of occupational expertise appears to be driven by the more prestigious and highly paid occupations, while in the other occupations it is estimated to have a negligible and insignificant contribution on earnings.

---

[31] The wage equation models are re-estimated this time using actual labour market experience instead of potential working experience. The findings (not presented here) suggest that general labour market skills have a significant and positive effect of around 20 per cent (ten-year effect), which however does not vary across the different occupations. The estimates on the other variables of interest remain similar to those presented in ***Table 3.4***.

Although the analysis in ***Section 3.4*** provides only weak evidence on the importance of industry specificity in the earnings profiles, I believe it is interesting to explore whether the significance of its role varies across the industry sectors. Therefore, in what follows I address this question by re-estimating a wage equation model with industry sector interaction terms. In particular, similar to what I do above, I consider an earnings equation where I include alongside the other regressors, interaction terms between the industry sectors (1-digit *SIC* classification) and the tenure, potential experience and industry experience polynomials. The findings are summarised in ***Tables 3.5*** and ***3.6***, where the estimated ten-year effects of the human capital variables of interest are presented. In addition, the p-value of a test that examines the significance of the variation (across the different industry sectors) in the estimates for each variable of interest is included as well. The results on the male workers in ***Table 3.5*** suggest some rather interesting patterns. The significance of seniority and employer-specific skills appears to vary across the industry sectors. The results almost uniformly suggest that tenure has a strong positive effect on earnings in the *agricultural*, the *energy* and the *mineral extraction* and *manufacture of metal and mineral products* industries. In addition there is weak evidence for the *construction* and *transport and communication* industries as well as for *other services*. Tenure in the other industry sectors does not appear to have any significant contribution on the earnings determination. The test also verifies that indeed the observed variation of tenure effect across the industries is significant. Overall, we see that the role of employer tenure crucially depends on the industry sector the individual is employed in. Particularly, employer-specific skills are highly rewarded mainly in '*blue-collar*' industries. About the returns to potential working experience, the findings suggest that despite the slight fluctuation in the estimated effects of the general labour market skills, their contribution in an earnings equation appears to be rather homogeneous across the various industry sectors. Industry experience in the majority of industries seems to play an insignificant role on workers' wages. There are two distinct cases though where industry specificity truly matters, but with opposite effects. Accumulated industry experience in the *metal goods, engineering and vehicles* industries is estimated to have a strong, negative though effect. I believe that the interpretation of this finding does not lie on the human capital theory but on some story associated with industry rents or business cycle. Although in my wage equation model I include industry dummy variables in order to capture any industry effect that may influence earnings, it is possible that the returns to industry experience, in this particular case, are in a way '*contaminated*' by what is happening that period in this specific industry sector. The negative returns to industry experience, for instance, may actually be reflecting the fact that a particular industry is going through a recession. One possible interpretation may be that this is a declining industry, where junior workers either are laid off or quit and senior workers (generally considered less mobile) are in a way '*trapped*' in their current sector. In this case, the negative industry experience contribution probably captures the effect of those senior workers who are unable to find a new job in a more prosperous industry[32]. On the other hand, the findings suggest that the accumulated industry-specific human capital in the *banking* sector has a significant positive effect on an individual's earnings profile. Finally, occupational experience is estimated to have a significant and positive impact in all cases examined.

[32] In order to further explore this issue, I re-estimate this wage equation model (the results are not presented here) including alternatively industry interaction terms with the time trend and the employment growth rate (over the last five years) of the individual's current industry sector. Although one would probably anticipate that the inclusion of these variables would '*correct*' the negative industry experience effect, the results are practically identical to the previous estimates. Overall, the findings from both the earnings equations remained fairly similar to those presented in *Table 3.5* (*Table 3.6* for the female employees).

Moving to the results on the female employees in ***Table 3.6*** we see that despite the variation in the estimates, employer tenure and potential labour market experience have a rather homogeneous impact on wages across the various industry sectors, as the performed tests suggest[33]. The role of industry experience, on the contrary, appears to vary across the different sectors. In particular, acquired industry-specific skills in the *banking* sector and in *other services* have a strong and positive effect on earnings, while in the majority of the other sectors it seems that industry specificity does not matter at all. Similar to the case of male employees, occupational experience is estimated to have a positive effect on earnings. Based on the analysis above, one conclusion that we may draw, concerning industry experience, is that on both male and female employees the banking sector seems to represent the main sector where industry specificity truly matters in the wage determination process.

Concluding the discussion, the findings suggest a particular pattern concerning the returns to accumulated occupation and industry specific skills. Although the analysis may not be exhaustive, the evidence presented in this section implies that occupational and industry specificity are mainly significant and noticeable in the more prestigious and high-paid occupations and industry sectors. Apparently, workers' expertise and consequently true productivity is what governs employees' earnings profiles in the more competitive and demanding sectors and occupations.

[33] The picture remains fairly identical when actual experience is included, instead of potential experience, in the wage equation model. Its estimated effect though is higher in this case.

3.6 Conclusion

In this chapter I depart from the assumption on the transferability of accumulated human capital that divides human capital dichotomously into employer-specific and general labour market skills, and pursue the idea of possible industry or occupational specificity. For the purpose of my analysis, I introduce two new variables, the industry and occupational experience that represent the accumulation of relevant skills and expertise over the years of employment. Their inclusion in a Mincer wage equation proves to be insightful on the workers' human capital-earnings paths. Occupation specific skills are estimated to have a rather important contribution in determining wages, highlighting the significance of '*specialisation*' in earnings profiles. The evidence, on the other hand, on industry specificity is not so strong and in some cases inconclusive. In addition, a further examination on occupational and industry specificity indicates that the observed patterns are actually driven by some particular occupations and industries, rejecting the hypothesis of homogeneity across them. Specifically, the findings outline that industry and occupational expertise is truly important for individuals' earnings in industry sectors and occupations that are characterised by high-paying, prestigious but, also competitive and demanding jobs, like *professional* and *managerial* jobs or jobs in the *banking* and *finance* sector. This analysis clearly provides evidence that supports the importance of occupational experience especially, which has been overlooked in the literature, and suggests some rather interesting patterns in the workers' earnings profiles.

Chapter 3: Tables

Table 3.1

Wage Equation Estimates on Male Employees

			1-digit	2-digit	1-digit	2-digit	1-digit	2-digit
OLS	T10	.085 (.031)	.075 (.031)	.066 (.031)	.062 (.031)	.059 (.032)	.055 (.031)	.046 (.032)
	PotExp10	.244 (.031)	.232 (.033)	.233 (.032)	.212 (.033)	.222 (.033)	.204 (.033)	.218 (.033)
	Ind10		.035 (.029)	.050 (.025)			.016 (.029)	.033 (.025)
	Occ10				.097 (.026)	.078 (.024)	.099 (.026)	.077 (.024)
	Adj. R^2	.536	.539	.539	.540	.539	.543	.542
GLS	T10	.083 (.017)	.075 (.017)	.067 (.017)	.065 (.017)	.064 (.017)	.059 (.017)	.052 (.017)
(I)	PotExp10	.276 (.024)	.271 (.025)	.268 (.024)	.248 (.025)	.261 (.024)	.246 (.025)	.256 (.024)
	Ind10		.034 (.016)	.051 (.013)			.025 (.016)	.043 (.014)
	Occ10				.077 (.014)	.060 (.013)	.073 (.015)	.053 (.014)
	Adj. R^2	.467	.470	.471	.475	.472	.477	.475
GLS	T10	.065 (.020)	.057 (.021)	.050 (.021)	.050 (.021)	.051 (.021)	.044 (.021)	.040 (.021)
(II)	PotExp10	.249 (.024)	.244 (.025)	.243 (.024)	.227 (.025)	.236 (.024)	.224 (.025)	.232 (.025)
	Ind10		.033 (.016)	.045 (.014)			.024 (.016)	.038 (.014)
	Occ10				.067 (.015)	.053 (.017)	.064 (.015)	.047 (.014)
	Adj. R^2	.469	.473	.473	.476	.474	.479	.477
FE	T10	.081 (.018)	.074 (.018)	.068 (.018)	.067 (.018)	.066 (.018)	.062 (.019)	.057 (.019)
(I)	PotExp10							
	Ind10		.034 (.017)	.049 (.014)			.027 (.017)	.043 (.014)
	Occ10				.061 (.015)	.046 (.013)	.057 (.015)	.038 (.014)
	Adj. R^2	.244	.245	.247	.248	.246	.248	.248
FE	T10	.033 (.032)	.025 (.032)	.023 (.032)	.022 (.032)	.025 (.032)	.017 (.032)	.018 (.032)
(II)	PotExp10							
	Ind10		.022 (.017)	.035 (.014)			.017 (.018)	.032 (.014)
	Occ10				.041 (.015)	.030 (.014)	.038 (.017)	.024 (.014)
	Adj. R^2	.216	.217	.218	.218	.217	.219	.218
Sample		5027						

Notes: 3rd order polynomial in employer-tenure, industry and occupational experience and 2nd order polynomial in potential labour market experience are considered. The estimated wage equation model also includes: age left education, a time trend, plus dummy variables for region, industry and occupation, establishment size, individual's qualifications, union coverage and union membership. Standard errors reported in brackets. In panel estimators (I), the observation unit is the individual. In panel estimators (II), the observation unit is the individual working for a particular employer. R^2 is defined as the within for the fixed-effects model and overall for the random-effects model.

Table 3.2

Wage Equation Estimates on Female Employees

			1-digit	2-digit	1-digit	2-digit	1-digit	2-digit
OLS	T10	.091	.050	.046	.039	.053	.017	.025
		(.037)	(.037)	(.036)	(.036)	(.037)	(.037)	(.037)
	PotExp10	.154	.113	.120	.098	.132	.082	.116
		(.037)	(.038)	(.036)	(.039)	(.038)	(.040)	(.036)
	Ind10		.082	.078			.057	.050
			(.037)	(.030)			(.036)	(.030)
	Occ10				.158	.091	.150	.100
					(.034)	(.029)	(.033)	(.027)
	Adj. R^2	.559	.575	.576	.575	.566	.583	.579
GLS	T10	.045	.033	.024	.030	.028	.022	.012
		(.020)	(.020)	(.020)	(.020)	(.020)	(.020)	(.021)
(I)	PotExp10	.135	.121	.121	.107	.117	.098	.109
		(.024)	(.025)	(.024)	(.025)	(.024)	(.025)	(.024)
	Ind10		.033	.054			.024	.044
			(.020)	(.016)			(.020)	(.017)
	Occ10				.075	.064	.073	.062
					(.017)	(.015)	(.017)	(.015)
	Adj. R^2	.495	.512	.514	.512	.504	.523	.519
GLS	T10	.081	.065	.056	.062	.062	.050	.043
		(.025)	(.025)	(.025)	(.025)	(.025)	(.025)	(.025)
(II)	PotExp10	.123	.106	.109	.098	.109	.085	.100
		(.024)	(.025)	(.024)	(.025)	(.024)	(.025)	(.024)
	Ind10		.043	.052			.036	.044
			(.020)	(.017)			(.020)	(.017)
	Occ10				.074	.051	.071	.049
					(.017)	(.015)	(.018)	(.015)
	Adj. R^2	.498	.516	.518	.517	.507	.527	.523
FE	T10	.015	.011	-.000	.008	.005	.005	-.006
		(.022)	(.023)	(.023)	(.022)	(.022)	(.023)	(.023)
(I)	PotExp10							
	Ind10		.023	.044			.016	.037
			(.021)	(.017)			(.021)	(.017)
	Occ10				.048	.048	.045	.043
					(.018)	(.015)	(.018)	(.015)
	Adj. R^2	.309	.310	.311	.312	.312	.312	.313
FE	T10	.137	.130	.124	.128	.127	.123	.118
		(.042)	(.042)	(.042)	(.042)	(.042)	(.042)	(.042)
(II)	PotExp10							
	Ind10		.029	.034			.023	.029
			(.022)	(.017)			(.022)	(.018)
	Occ10				.036	.031	.033	.027
					(.018)	(.015)	(.019)	(.015)
	Adj. R^2	.275	.276	.276	.276	.276	.277	.277
Sample		3587						

Notes: 3rd order polynomial in employer-tenure, industry and occupational experience and 2nd order polynomial in potential labour market experience are considered. The estimated wage equation model also includes: age left education, a time trend, plus dummy variables for region, industry and occupation, establishment size, individual's qualifications, union coverage and union membership. Standard errors reported in brackets. In panel estimators (I), the observation unit is the individual. In panel estimators (II), the observation unit is the individual working for a particular employer. R^2 is defined as the within for the fixed-effects model and overall for the random-effects model.

Table 3.3

Wage Equations with Occupational Interaction Terms (Male Employees)	OLS	GLS (I)	GLS (II)	FE (I)	FE (II)
T10 (soc1)	-.003	-.041	-.074	.005	-.028
	(.092)	(.034)	(.038)	(.035)	(.048)
T10 (soc2)	.080	.077	.038	.112	.055
	(.079)	(.043)	(.047)	(.043)	(.053)
T10 (soc3)	.014	.017	.007	.021	6.92e-04
	(.072)	(.044)	(.049)	(.044)	(.054)
T10 (soc4)	.128	.130	.106	.146	.069
	(.087)	(.049)	(.052)	(.049)	(.057)
T10 (soc5)	.151	.104	.141	.072	.059
	(.057)	(.036)	(.039)	(.037)	(.047)
T10 (soc6)	.170	.112	.106	.049	-.011
	(.134)	(.067)	(.068)	(.070)	(.074)
T10 (soc7)	.040	.018	.017	.056	-.023
	(.124)	(.071)	(.076)	(.072)	(.087)
T10 (soc8)	.035	.079	.058	.076	-.016
	(.061)	(.037)	(.040)	(.037)	(.047)
T10 (soc9)	.197	.036	.008	-.055	-.155
	(.085)	(.071)	(.073)	(.072)	(.079)
Test (p-value)	0.671	0.072	0.073	0.116	0.261
PotExp10 (soc1)	.287	.220	.200		
	(.081)	(.050)	(.051)		
PotExp10 (soc2)	.198	.261	.196		
	(.088)	(.056)	(.059)		
PotExp10 (soc3)	.148	.186	.153		
	(.089)	(.053)	(.054)		
PotExp10 (soc4)	.324	.312	.298		
	(.069)	(.055)	(.056)		
PotExp10 (soc5)	.209	.267	.244		
	(.060)	(.044)	(.044)		
PotExp10 (soc6)	.394	.336	.292		
	(.137)	(.084)	(.083)		
PotExp10 (soc7)	.299	.368	.367		
	(.118)	(.081)	(.081)		
PotExp10 (soc8)	.053	.180	.183		
	(.075)	(.049)	(.050)		
PotExp10 (soc9)	.134	.201	.196		
	(.074)	(.085)	(.086)		
Test (p-value)	0.099	0.205	0.224		
Ind10	.028	.039	.034	.036	.026
	(.028)	(.016)	(.017)	(.017)	(.018)
Occ10 (soc1)	.303	.257	.268	.184	.168
	(.071)	(.034)	(.035)	(.036)	(.039)
Occ10 (soc2)	.143	.088	.060	.045	.007
	(.078)	(.044)	(.045)	(.046)	(.049)
Occ10 (soc3)	.149	.073	.060	.035	.012
	(.070)	(.042)	(.042)	(.044)	(.045)
Occ10 (soc4)	-.082	.017	.013	.042	.053
	(.081)	(.047)	(.048)	(.048)	(.050)
Occ10 (soc5)	.015	.010	-.013	.037	.007
	(.062)	(.040)	(.040)	(.042)	(.043)
Occ10 (soc6)	-.100	-.043	-.026	-.032	-.019
	(.116)	(.066)	(.065)	(.070)	(.070)
Occ10 (soc7)	.291	.113	.150	.019	.064
	(.127)	(.074)	(.073)	(.073)	(.077)
Occ10 (soc8)	-.014	.025	-.005	.030	-.026
	(.054)	(.037)	(.038)	(.039)	(.040)
Occ10 (soc9)	-.012	-.064	-.071	.021	.035
	(.076)	(.068)	(.067)	(.075)	(.075)
Test (p-value)	0.001	0.000	0.000	0.028	0.021

(*Table 3.3 continued*)					
Adj. R^2	.565	.502	.506	.263	.233

Notes: The estimated wage equation model includes: 3rd order polynomial in employer-tenure, industry and occupational experience and 2nd order polynomial in potential labour market experience, interaction terms between 1-digit occupational dummies and the tenure, potential labour market experience and occupational experience polynomials, age left education, a time trend, plus dummy variables for region, industry and occupation, establishment size, individual's qualifications, union coverage and union membership. Standard errors reported in brackets. In panel estimators (I), the observation unit is the individual. In panel estimators (II), the observation unit is the individual working for a particular employer. R^2 is defined as the within for the fixed-effects model and overall for the random-effects model. Classification of occupations in Appendix. Performed test on equality of estimated effect across occupations.

Table 3.4

Wage Equations with Occupational Interaction Terms (Female Employees)

	OLS	GLS (I)	GLS (II)	FE (I)	FE (II)
T10 (soc1)	-.107	-.041	-.054	-.039	-.004
	(.087)	(.042)	(.046)	(.043)	(.063)
T10 (soc2)	-.123	.020	.028	.071	.164
	(.102)	(.048)	(.050)	(.050)	(.059)
T10 (soc3)	.098	.089	.109	.057	.137
	(.088)	(.042)	(.044)	(.043)	(.059)
T10 (soc4)	.006	.019	.035	-.020	.055
	(.051)	(.031)	(.035)	(.033)	(.055)
T10 (soc5)	-.067	-.121	.025	-.114	.054
	(.145)	(.104)	(.114)	(.097)	(.116)
T10 (soc6)	.176	.002	.044	-.035	.029
	(.123)	(.055)	(.061)	(.058)	(.078)
T10 (soc7)	.191	.071	.122	-.043	.056
	(.105)	(.088)	(.089)	(.084)	(.097)
T10 (soc8)	.112	.136	.148	-.003	-.044
	(.162)	(.100)	(.108)	(.103)	(.124)
T10 (soc9)	-.057	.004	.065	-.027	.052
	(.163)	(.122)	(.123)	(.119)	(.127)
Test (p-value)	0.177	0.240	0.180	0.419	0.189
PotExp10 (soc1)	.224	.136	.124		
	(.096)	(.048)	(.049)		
PotExp10 (soc2)	.209	.181	.197		
	(.118)	(.058)	(.060)		
PotExp10 (soc3)	-.021	.024	.030		
	(.067)	(.042)	(.044)		
PotExp10 (soc4)	.215	.083	.088		
	(.073)	(.040)	(.040)		
PotExp10 (soc5)	-.014	.173	.104		
	(.094)	(.113)	(.113)		
PotExp10 (soc6)	-.142	.062	.021		
	(.113)	(.062)	(.062)		
PotExp10 (soc7)	-.114	.037	-.023		
	(.102)	(.089)	(.097)		
PotExp10 (soc8)	-.150	.003	.084		
	(.121)	(.105)	(.108)		
PotExp10 (soc9)	-.043	-.016	-.032		
	(.098)	(.090)	(.092)		
Test (p-value)	0.045	0.139	0.073		
Ind10	.049	.032	.043	.008	.016
	(.038)	(.021)	(.021)	(.022)	(.023)
Occ10 (soc1)	.269	.086	.111	-.028	.013
	(.077)	(.041)	(.043)	(.045)	(.048)
Occ10 (soc2)	.175	.115	.129	-.008	-.039
	(.094)	(.054)	(.055)	(.057)	(.062)
Occ10 (soc3)	.148	.172	.153	.138	.097
	(.087)	(.042)	(.042)	(.045)	(.047)

(*Table 3.4 continued*)					
Occ10 (soc4)	.105	.067	.047	.073	.030
	(.059)	(.045)	(.047)	(.043)	(.047)
Occ10 (soc5)	.029	-.021	-.016	-.110	-.094
	(.143)	(.102)	(.105)	(.111)	(.125)
Occ10 (soc6)	.213	.077	.056	.078	.050
	(.141)	(.060)	(.060)	(.059)	(.060)
Occ10 (soc7)	-.045	-.040	-.078	-.028	-.057
	(.116)	(.083)	(.083)	(.085)	(.085)
Occ10 (soc8)	-.309	-.143	-.039	.024	.181
	(.113)	(.096)	(.104)	(.099)	(.115)
Occ10 (soc9)	.341	.034	.032	-.080	-.075
	(.165)	(.129)	(.127)	(.136)	(.134)
Test (p-value)	0.002	0.041	0.169	0.118	0.361
Adj. R^2	.616	.546	.549	.335	.298

Notes: The estimated wage equation model includes: 3rd order polynomial in employer-tenure, industry and occupational experience and 2nd order polynomial in potential labour market experience, interaction terms between 1-digit occupational dummies and the tenure, potential labour market experience and occupational experience polynomials, age left education, a time trend, plus dummy variables for region, industry and occupation, establishment size, individual's qualifications, union coverage and union membership. Standard errors reported in brackets. In panel estimators (I), the observation unit is the individual. In panel estimators (II), the observation unit is the individual working for a particular employer. R^2 is defined as the within for the fixed-effects model and overall for the random-effects model. Classification of occupations in Appendix. Performed test on equality of estimated effect across occupations.

Table 3.5

Wage Equations with Industry Interaction Terms (Male Employees)

	OLS	GLS (I)	GLS (II)	FE (I)	FE (II)
T10 (sic1)	.116	.168	.221	.156	.127
	(.107)	(.070)	(.073)	(.072)	(.082)
T10 (sic2)	.020	.099	.153	.133	.227
	(.110)	(.064)	(.073)	(.063)	(.083)
T10 (sic3)	-.063	-.001	.015	.037	.027
	(.060)	(.037)	(.041)	(.039)	(.050)
T10 (sic4)	-.058	-.020	-5.66e-04	-.005	-.033
	(.076)	(.043)	(.047)	(.043)	(.056)
T10 (sic5)	.245	.112	.066	.101	.007
	(.093)	(.067)	(.069)	(.067)	(.074)
T10 (sic6)	.198	.045	.042	.016	-.061
	(.091)	(.045)	(.048)	(.047)	(.057)
T10 (sic7)	.034	.172	.085	.203	.034
	(.083)	(.053)	(.058)	(.055)	(.067)
T10 (sic8)	.114	.019	-.049	.031	-.041
	(.129)	(.046)	(.050)	(.047)	(.058)
T10 (sic9)	.087	.082	.087	.054	.021
	(.058)	(.034)	(.037)	(.036)	(.047)
Test (p-value)	0.054	0.037	0.046	0.043	0.039
PotExp10 (sic1)	.135	.189	.094		
	(.130)	(.091)	(.093)		
PotExp10 (sic2)	.179	.274	.234		
	(.115)	(.077)	(.078)		
PotExp10 (sic3)	.251	.310	.284		
	(.058)	(.047)	(.049)		
PotExp10 (sic4)	.144	.235	.234		
	(.086)	(.050)	(.051)		
PotExp10 (sic5)	.249	.190	.195		
	(.107)	(.074)	(.075)		
PotExp10 (sic6)	.346	.367	.390		
	(.078)	(.051)	(.052)		

(*Table 3.5 continued*)					
PotExp10 (sic7)	.166 (.116)	.228 (.068)	.190 (.072)		
PotExp10 (sic8)	.214 (.096)	.263 (.059)	.199 (.062)		
PotExp10 (sic9)	.207 (.073)	.198 (.047)	.178 (.048)		
Test (p-value)	0.690	0.282	0.046		
Ind10 (sic1)	.240 (.108)	.062 (.079)	.001 (.080)	.090 (.083)	.027 (.085)
Ind10 (sic2)	.296 (.113)	.049 (.070)	.059 (.069)	-.052 (.070)	-.114 (.072)
Ind10 (sic3)	-.155 (.055)	-.130 (.043)	-.140 (.043)	-.082 (.046)	-.094 (.048)
Ind10 (sic4)	.021 (.065)	.040 (.044)	.028 (.045)	.029 (.047)	.021 (.049)
Ind10 (sic5)	-.121 (.079)	.042 (.065)	.029 (.066)	.053 (.067)	.058 (.069)
Ind10 (sic6)	-.097 (.086)	.003 (.049)	.003 (.050)	.083 (.052)	.119 (.054)
Ind10 (sic7)	-.029 (.082)	-.072 (.057)	-.033 (.060)	-.105 (.063)	-.077 (.072)
Ind10 (sic8)	.086 (.126)	.178 (.050)	.230 (.051)	.103 (.054)	.080 (.060)
Ind10 (sic9)	-.016 (.070)	.043 (.040)	.019 (.040)	.078 (.045)	.042 (.047)
Test (p-value)	0.002	0.001	0.000	0.052	0.042
Occ10	.107 (.025)	.076 (.015)	.068 (.015)	.059 (.015)	.038 (.016)
Adj. R^2	.571	.501	.503	.271	.242

Notes: The estimated wage equation model includes: 3[rd] order polynomial in employer-tenure, industry and occupational experience and 2[nd] order polynomial in potential labour market experience, interaction terms between 1-digit industry dummies and the tenure, potential labour market experience and industry experience polynomials, age left education, a time trend, plus dummy variables for region, industry and occupation, establishment size, individual's qualifications, union coverage and union membership. Standard errors reported in brackets. In panel estimators (I), the observation unit is the individual. In panel estimators (II), the observation unit is the individual working for a particular employer. R^2 is defined as the within for the fixed-effects model and overall for the random-effects model. Classification of occupations in Appendix. Performed test on equality of estimated effect across occupations.

Table 3.6

Wage Equations with Industry Interaction Terms (Female Employees)

	OLS	GLS (I)	GLS (II)	FE (I)	FE (II)
T10 (sic1)	.310 (.148)	.285 (.127)	.229 (.138)	.156 (.133)	.148 (.160)
T10 (sic2)	-.071 (.203)	.095 (.153)	.048 (.163)	.054 (.170)	-.035 (.208)
T10 (sic3)	-.053 (.106)	-.016 (.069)	.073 (.079)	.014 (.071)	.173 (.098)
T10 (sic4)	-.214 (.123)	-.009 (.074)	.057 (.077)	-.041 (.076)	.079 (.092)
T10 (sic5)	-.140 (.256)	.473 (.376)	.558 (.373)	.691 (.327)	.836 (.326)
T10 (sic6)	.064 (.071)	.117 (.044)	.138 (.048)	.048 (.047)	.080 (.068)
T10 (sic7)	.340 (.221)	.076 (.124)	.076 (.139)	.352 (.149)	.557 (.219)
T10 (sic8)	.003 (.091)	.036 (.046)	.050 (.050)	-.005 (.051)	.051 (.075)

(*Table 3.6 continued*)

T10 (sic9)	-.012 (.050)	-.040 (.027)	-.005 (.031)	-.041 (.031)	.079 (.047)
Test (p-value)	0.119	0.259	0.676	0.127	0.128
PotExp10 (sic1)	-.078 (.266)	-.128 (.164)	.243 (.202)		
PotExp10 (sic2)	.091 (.170)	.088 (.145)	-.024 (.152)		
PotExp10 (sic3)	.348 (.108)	.167 (.080)	.056 (.084)		
PotExp10 (sic4)	.135 (.109)	.078 (.068)	.081 (.075)		
PotExp10 (sic5)	.449 (.241)	.176 (.322)	.053 (.318)		
PotExp10 (sic6)	-.055 (.094)	.044 (.047)	.013 (.049)		
PotExp10 (sic7)	-.351 (.277)	-2.53e-04 (.143)	-.026 (.159)		
PotExp10 (sic8)	.201 (.076)	.154 (.049)	.166 (.052)		
PotExp10 (sic9)	.074 (.056)	.066 (.033)	.060 (.033)		
Test (p-value)	0.030	0.505	0.467		
Ind10 (sic1)	-.028 (.158)	.016 (.117)	.081 (.131)	.025 (.127)	.092 (.165)
Ind10 (sic2)	-.153 (.166)	.070 (.122)	.159 (.137)	.163 (.132)	.335 (.178)
Ind10 (sic3)	-.113 (.112)	-.111 (.080)	.002 (.085)	-.164 (.084)	-.153 (.104)
Ind10 (sic4)	.063 (.087)	-.018 (.073)	-.010 (.075)	-.037 (.078)	.003 (.081)
Ind10 (sic5)	-2.45 (2.89)	.940 (2.84)	.769 (2.77)	1.68 (2.61)	1.47 (2.54)
Ind10 (sic6)	-.048 (.128)	-.092 (.051)	-.102 (.052)	-.058 (.052)	-8.24e-04 (.056)
Ind10 (sic7)	.062 (.201)	.102 (.139)	.075 (.145)	-.257 (.180)	-.336 (.234)
Ind10 (sic8)	.188 (.084)	.173 (.052)	.188 (.054)	.138 (.055)	.130 (.063)
Ind10 (sic9)	.116 (.055)	.106 (.037)	.106 (.038)	.032 (.042)	-.004 (.046)
Test (p-value)	0.339	0.012	0.018	0.027	0.127
Occ10	.152 (.032)	.071 (.018)	.072 (.018)	.040 (.018)	.034 (.019)
Adj. R^2	.610	.543	.547	.339	.301

Notes: The estimated wage equation model includes: 3rd order polynomial in employer-tenure, industry and occupational experience and 2nd order polynomial in potential labour market experience, interaction terms between 1-digit industry dummies and the tenure, potential labour market experience and industry experience polynomials, age left education, a time trend, plus dummy variables for region, industry and occupation, establishment size, individual's qualifications, union coverage and union membership. Standard errors reported in brackets. In panel estimators (I), the observation unit is the individual. In panel estimators (II), the observation unit is the individual working for a particular employer. R^2 is defined as the within for the fixed-effects model and overall for the random-effects model. Classification of occupations in Appendix. Performed test on equality of estimated effect across occupations.

Chapter 3: Appendix

Table A.3.1

Sample Characteristics (BHPS): Waves 1-8				
	Male		Female	
No. of Individuals	985		734	
No. of Observations	5027		3587	
No. of Employer Changes	1155		850	
No. of Industry Changes (1-digit)	1347		909	
No. of Industry Changes (2-digit)	1584		1068	
No. of Occupational Changes (1-digit)	1502		1005	
No. of Occupational Changes (2-digit)	1770		1256	
No. of Industry Changes (1-digit) per ind.†	2.24		2.19	
No. of Industry Changes (2-digit) per ind.†	2.41		2.31	
No. of Occupational Changes (1-digit) per ind.†	2.27		2.24	
No. of Occupational Changes (2-digit) per ind.†	2.86		2.55	
	%		%	
Individuals who Changed Industry (1-digit)	29.6		20.0	
Individuals who Changed Industry (2-digit)	43.0		34.6	
Individuals who Changed Occupation (1-digit)	41.2		29.7	
Individuals who Changed Occupation (2-digit)	50.3		45.8	
	Mean	(S.D.)	Mean	(S.D)
Employer Tenure	7.64	(6.53)	6.40	(5.09)
Industry Experience (1-digit)	13.26	(9.83)	11.96	(8.26)
Industry Experience (2-digit)	10.66	(9.33)	9.40	(7.70)
Occupational Experience (1-digit)	11.37	(9.78)	11.21	(8.70)
Occupational Experience (2-digit)	8.95	(9.09)	8.38	(7.86)
Potential Labour Market Experience	22.45	(10.43)	21.76	(10.81)
Actual Labour Market Experience (full-time)	21.83	(10.39)	14.98	(7.95)

Table A.3.2

Regressors
Employer tenure (cubic)
Total labour market experience (quadratic)
Industry experience (cubic)
Occupational experience (cubic)
Age left education
Individual's skills (dummies)
Time trend
Region (dummies)
Industry (1-digit dummies)
Establishment size (dummies)
Occupation (dummies)
Qualification (dummies)
Union Coverage (dummy)
Union Membership (dummy)

Table A.3.3

	Industry Classification (1-digit)
SIC1	Agriculture, Forestry & Fishing; Energy & Water Supplies
SIC2	Extraction of Minerals & Ores (other than fuels); Manufacture of Metals, Mineral Products & Chemicals
SIC3	Metal Goods, Engineering & Vehicles Industries
SIC4	Other Manufacturing Industries
SIC5	Construction
SIC6	Distribution, Hotels & Catering (Repairs)
SIC7	Transport & Communication
SIC8	Banking, Finance, Insurance, Business Services & Leasing
SIC9	Other Services

Table A.3.4

	Occupational Classification (1-digit)
SOC1	Managers & Administrators
SOC2	Professional Occupations
SOC3	Associate Professional & Technical Occupations
SOC4	Clerical & Secretarial Occupations
SOC5	Craft & Related Occupations
SOC6	Personal & Protective Service Occupations
SOC7	Sales Occupations
SOC8	Plant & Machine Operatives
SOC9	Other Occupations

Table A.3.5

Industry and Occupational Distribution (Male Employees)											
	SIC1	SIC2	SIC3	SIC4	SIC5	SIC6	SIC7	SIC8	SIC9	Total	%
SOC1	25	37	113	82	54	148	86	137	192	874	17.4
SOC2	18	9	124	8	18	5	8	101	301	592	11.8
SOC3	15	16	58	35	14	6	40	128	220	532	10.6
SOC4	35	24	27	24	10	79	30	76	79	384	7.6
SOC5	98	63	265	214	89	130	47	7	64	977	19.4
SOC6	3	0	1	22	0	35	15	26	283	385	7.7
SOC7	0	9	39	19	6	90	3	30	0	196	3.9
SOC8	37	90	158	247	15	62	123	12	45	789	15.7
SOC9	73	3	6	5	20	12	144	3	32	298	5.9
Total	304	251	791	656	226	567	496	520	1216	5027	
%	6.1	5.0	15.7	13.0	4.5	11.3	9.9	10.3	24.2		100

Table A.3.6

Industry and Occupational Distribution (Female Employees)											
	SIC1	SIC2	SIC3	SIC4	SIC5	SIC6	SIC7	SIC8	SIC9	Total	%
SOC1	5	6	18	36	3	125	8	82	200	483	13.4
SOC2	1	2	4	3	2	4	3	37	406	462	12.9
SOC3	2	5	25	17	4	15	3	58	389	518	14.4
SOC4	45	21	100	83	9	152	79	311	441	1241	34.6
SOC5	1	16	5	83	0	3	0	0	9	117	3.3
SOC6	0	0	0	0	1	44	7	7	296	355	9.9
SOC7	3	1	1	4	0	120	0	6	4	139	3.9
SOC8	1	25	54	40	0	10	1	0	2	133	3.7
SOC9	5	8	3	7	0	32	14	4	66	139	3.9
Total	63	84	210	273	19	505	115	505	1813	3587	
%	1.8	2.3	5.9	7.6	0.5	14.1	3.2	14.1	50.5		100

Construction of Industry and Occupational Experience Variable

The construction of both industry and occupational experience is quite similar. Therefore here I focus my attention on the steps followed in order to construct the industry experience. One should be able to derive occupational experience as well by simply repeating this process.

The starting point (*1st step*) on the construction of the industry experience is *Wave 3*, where retrospective information on respondents' employment history is collected (*CLIFEJOB*). This is a record that contains information about jobs held in employment spells, covering the period from the time individuals first left full-time education since the 1st September 1990, where the collection of data in the main panel began (*AJOBHIST* record). *CLIFEJOB* record is restricted to respondents that were interviewed at *Wave 2* and had another (full-time or part-time) paid job (with different employer than the one in their previous employment spell) at *Wave 3* that lasted more than one month. The construction of industry experience is based on this record since it is the only lifetime employment status history record in BHPS that provides information on the industry respondents were employed[34]. Therefore, industry experience can be constructed only for those individuals included in the *CLIFEJOB* record.

First, I restrict my attention to those who reported being either part-time or full-time employees, excluding the self-employed respondents. Then I calculate the employment spells based on the recorded length of job history spells, or based on the

[34] The *BLIFEMST* record which contains information about employment status spells, covering the period since the respondent first left full-time education, does not provide any information on the industry the individual was employed.

information about the beginning and the end of these spells. When seasons are reported, they are replaced with months[35]. Information on the industry is collected when reported. In the case of missing information, I check the *CINDRESP* record, only though when the starting date of employment matches between these two records, or when the current job in *CINDRESP* began before the employment spell of interest in the *CLIFEJOB*. Alternatively, I gather this information from the following waves (*4-8*). The criterion is that the starting date of the reported current employment spell should either coincide or be before the date the spell in *CLIFEJOB* began. Finally, I check whether the starting date current job in *Waves 1 & 2* matches exactly with the date the employment spell in *CLIFEJOB* has began, since I can get information on industry from these waves. After constructing the employment spells and collecting the related information on industry, I add up the spells by industry for each respondent separately in order to construct the industry experience and keep the most recent one, since individuals may be repeated in the sample. In the next step, I use the already calculated industry experience as the basis for the construction of industry experience in *Wave 1*.

The industry experience variable constructed up to this point refers to employment spells of the respondents' labour market history, where the last reported employment spell began before the 1st September 1990 and may have terminated either before or after the date of *Wave 1* interview. Therefore I need to identify which is the case, for each individual, and based on this information and the already constructed variable above to measure the industry experience up to the *Wave 1* interview (*2nd step*). Based on the *AJOBHIST* record, which contains information from the employment history over the period from 1st September of the year before

35 '*Winter*' is replaced with January, '*Spring*' with April, '*Summer*' with July and '*Autumn*' with October.

to the date of interview, the sample is divided into four groups, according to the individuals' status type of the last job history record. This is quite informative on what to expect in the following waves.

Not Last Spell:

- If the most recent employment spell (in a different job but with the same employer, or with a different employer) in *AJOBHIST* ended when the last employment spell in *CLIFEJOB* terminated, or afterwards but before the *Wave 1* interview, then the industry-experience variable in *Wave 1* is the one calculated in the ***1st step.***
- If it ended after the *Wave 1* interview, then the period between the end of the last employment spell (in *CLIFEJOB* record) and the date of interview is subtracted from the measured above variable.
- If the last employment spell in *CLIFEJOB* ended before the most recent one in *AJOBHIST*, then the duration of any additional employment spells from the latter record is included in the variable of the ***1st step*** and that gives the *Wave 1* industry-experience.

Last Job Ever:

- If the most recent job spell in *AJOBHIST* did not end after the date the last employment status in *CLIFEJOB* ended or the *Wave 1* interview, the industry-experience in that wave coincides with the one already measured above.
- Otherwise, the duration between the date of interview and the termination of the *CLIFEJOB* last job spell should be subtracted from the variable of the ***1st step.***

Began After 1.9.90

- If at the most recent employment spell in *AJOBHIST* the end date is before or at the same time that the last spell in *CLIFEJOB* began, then *Wave 1* industry experience is equal to the one already calculated after subtracting the duration of this last spell.
- If the beginning though of the most recent spell in *AJOBHIST* matches with the beginning of the last spell in *CLIFEJOB*, then industry experience in *Wave 1* should be equal to the already calculated industry experience minus the period between the *Wave 1* and *3* interviews.

Present Job (Started) Before 1.9.90

- Similar to the previous case.

For the remained individuals, the construction of industry-experience is based on *AINDRESP* record, the main *Wave 1* record. The sample is divided into three main groups according to their employment status:

1. If individuals not currently employed, then industry-experience is equal to the one calculated in the *1st step.*
2. If the beginning of the current employment in *Wave 1* matches with the beginning of the last spell in *CLIFEJOB*, then industry experience in this wave is equal to the one already estimated, minus the duration of this last spell, plus the period between the beginning of the current job and the *Wave 1* interview.
3. The last group of interest contains those individuals whose current job began after the date the last spell in *CLIFEJOB* started. There are six sub-cases considered here. If the last spell in *CLIFEJOB*:

- Finished after the ***Wave 1*** interview, then industry experience is equal to the industry experience from the ***1st step***, minus the last spell, plus the period between the end of this last spell and the ***Wave 1*** interview.
- Finished before or during the beginning of the current employment in ***Wave 1***, then industry experience is equal to the calculated one, plus the period between the start of current job and the ***Wave 1*** interview.
- Started after the beginning of the current employment, but before the date of interview, then ***Wave 1*** industry experience is equal to the variable from the ***1st step***, minus this last spell, plus the period between the beginning of this last spell and the ***Wave 1*** interview.
- Ended before or during the ***Wave 1*** interview, then industry experience is equal to the one measured in the ***1st step***, plus the period between the end of this last spell and the date of interview.
- Ended after the ***Wave 1*** interview, then industry experience is equal to the industry experience based on the ***1st step***, minus the period between the date of interview and the end of this last spell.

For the remained individuals, industry experience is equal to the one estimated before, minus the last spell in that record, plus the period between the start of current job in ***Wave 1*** and the date of interview. The construction of the ***Wave 1*** industry experience is completed here. The calculation of industry experience for the following waves is based on this one.

The methodology employed for the construction of the industry experience for the remaining waves (***3rd step***) is the same for all of them. Therefore, I only discuss how to proceed on ***Wave 2*** and the analysis should be exactly the same for the rest of the waves (***3-8***).

Focusing first on the ***BJOBHIST*** record, the individuals of interest here are those in a different job but with the same employer or those working full-time or part-time for a different employer. The first group of respondents includes those, whose least recent employment spell in ***BJOBHIST*** began before and ended after or during the ***Wave 1*** date of interview. Industry experience is equal to the one in ***Wave 1*** plus the period between the ***Wave 1*** interview and the end of this employment spell, the duration of the following spells of employment and the period between the beginning of the current employment spell, reported in ***BINDRESP***, and the date of ***Wave 2*** interview. The second group contains the respondents who did not report any employment spell in ***BJOBHIST***. For those individuals, industry experience is equal to the one in ***Wave 1*** if they reported not employed as well in ***BINDRESP***. Otherwise in the case of employment, it should be equal to the ***Wave 1*** industry experience plus the period between the beginning of their current employment and the ***Wave 2*** interview. For the remained individuals in record ***BINDRESP***, industry experience is equal to the ***Wave 1*** industry experience plus the period between ***Waves 1*** and ***2*** interviews if they reported employed and equal to the ***Wave 1*** industry experience if they were not currently working. The construction of industry experience for the remained waves is exactly the same as the one described above.

Occupational experience is constructed exactly as industry experience. The spells are identified in a similar pattern and the only difference is that instead of using information on the industry individuals are working in, here I use the occupation of the individual reported in each employment spell, in order to estimate the period of time spent in each occupation.

Chapter 4

4 Seniority Profiles in Unionised Workplaces: Do Unions Still Have the Edge?

4.1 Introduction

Numerous studies in the literature have examined the significance of seniority on the wage determination process. Job tenure, either due to unobserved individual and job-match characteristics reflected in the duration of the job match (Abraham and Farber 1987a; Altonji and Shakotko 1987) or due to the acquisition of firm-specific human capital (Topel 1991), appears to have a positive impact on earnings. My empirical study on tenure-wage growth in *Chapter 2* also suggests a modest but positive tenure effect. In addition, the analysis based on quantile regressions indicates that, at least for the male employees, seniority is rewarded more at the lower parts of the wage distribution, rejecting the homogeneity hypothesis on the tenure effect. The purpose of this chapter is to extend this knowledge and explore whether there is any interaction between institutional arrangements and workplace policies on individuals' earnings profiles, giving a particular attention to seniority. More specifically, I wish to examine whether there are different seniority-earnings paths when a trade union is present or when formal wage incremental policies exist in the workplace. The innovation of this chapter is that it is based on a more detailed description of the different, accumulated in-work kinds of skills that basically decompose acquired human capital beyond the conventional practice of dividing skills between firm-specific and general labour market skills. Already the analysis in *Chapter 3* highlights the significance of occupational expertise on individuals' earnings profiles, whilst there is limited evidence that industry specific skills may have a modest role as well. Furthermore, here I use British panel data covering the last decade of the twentieth century, a period of time well after the hostile legislation towards unionism (end of 1970s) and just before the introduction of a national minimum wage (April 1999). I believe it is of great interest to examine the role of unions and their effect on earnings in the modern British labour market and to explore how trade unions adjusted to this new era.

The British labour market since the late 1970s has experienced many significant changes concerning employees' representation in the workplace. Restrictive legislation and less friendly managerial attitudes towards trade unions among other developments led to the weakening of unionism through the derecognition of such workers' associations in existing establishments, the creation of new workplaces where trade unions were not particularly popular, or supported and the decline in union membership. Consequently, the proportion of the workforce covered by collective bargaining shrunk and, in line with the decline in membership strength, union influence over pay setting has waned even where the institution continues to exist. Union membership declined by over 5 million in the two decades after the 1979 zenith of 13 million. In addition the proportion of workers covered by a collective agreement fell from 71 per cent in 1984 to 51 percent in 1990 and to 35 per cent in 1997. The wage premium that individuals covered by collective contracts traditionally used to enjoy over the workers who were not covered has effectively evaporated by the end of the 1990s. For men the wage premium fell from 9 per cent in 1991 to zero in 1999, while for women, it fell from 16 per cent to 10 per cent over the eight years (Machin, 2002). Although, trade unions in nowadays appear to be less able to extract concessions from employers and the union wage premium may be nearly extinct, still workers' unions and collective contracts continue to be strongly associated with lower levels of earnings inequality than the non-union sector (Metcalf *et al.*, 2001).

Despite the fact that the impact of trade unions on economic performance has been restricted in recent years, unions still wield '*the sword of justice*' in the workplace. It is a stylised fact that pay dispersion among unionised workers is lower than the spread among their non-union counterparts. Trade unions even now sustain their traditional role as defenders of egalitarian pay structures in the organised sector (Machin, 1997). This is achieved through three avenues identified in the literature: (a) within establishments (b) across workplaces and firms and (c) across the whole pay distribution. Unions reduce wage dispersion within establishments via two operational rules. First, they prefer a single wage rate for each occupational group whereas in workplaces with no representation and collective contracts supervisors decide pay levels within a range. Second, unionised workplaces make more use of objective criteria, like seniority, in setting pay rather than subjective factors, like individual merit, preferred in non-union establishments. Union representatives prefer reduced pay differentials within an establishment for three main reasons:

1. They are concerned about favouritism and discrimination in the workplace, therefore they opt for impartial objective standards where pay goes with the job.
2. In a median voter framework of union representation, since median pay is less than mean pay in nearly all firms, we should expect that over half of the employees will favour redistribution towards the lower paid.
3. Workers' solidarity is likely to strengthen when they receive similar wage rates.

The pursuit of wage standardisation by trade unions narrows pay dispersion within the organised sector as well. Two arguments that provide reasoning for this phenomenon (Freeman and Medoff, 1984) are that, first of all, employers and workers of firms competing in the same market can be expected to favour a standard rate. On the one hand, an employer does not want a labour contract that is more expensive than its competitors. And on the other hand, it secures workers' pay from any undercutting, since essentially it takes wages out of competition.

Furthermore, union solidarity may be at stake if some workers are paid notably more than others for the same job. The decentralisation of bargaining from national multi-employer agreements to firm or workplace agreements, especially in the private sector, and the privitisation during the last two decades (British Petroleum, British Aerospace, British Telecom, gas water, electricity and the railways) may have increased the dispersion of pay in the organised sector. Nevertheless, continuing union recognition should prevent pay dispersion widening to the extent that we observe in the non-unionised sector. Finally, trade unions reduce inequality across the whole pay distribution by the enforcement of a *de facto* wage floor for covered jobs, i.e. by truncating the bottom tail of their pay distribution. The introduction though of a national minimum wage (NMW) legislation (April 1999) may undermine collective bargaining where it exists and effectively reduce the role of trade unions in the future[36].

Trade unions are traditionally associated with the standardisation of pay setting mechanisms, often in the form of seniority pay scales. Seniority can be considered a mechanism that unions adopt in order to enforce non-arbitrary procedures for pay and promotion and so any pay differentials arising out of seniority based systems are compatible with union goals. Freeman and Medoff (1984) underline the importance of seniority in the operation of a unionised workplace. According to the authors, "*union seniority clauses protect older union workers from the danger of layoffs and give them greater chances of promotion compared with otherwise similar older nonunion workers*" (pp. 135). A theory that provides an insight into how seniority is directly linked to wages in a union firm is the '*discriminating monopoly*' approach that describes a non-uniform pricing model of union wages (Frank 1985;

[36] The data set used here covers the period between 1991 and 1998, where there was no statutory minimum wage protection, so the NMW does not invalidate any of my arguments.

Kuhn 1988; Kuhn and Robert 1989; Frank and Malcomson 1994). This model is similar to the multi-part tariff in product markets, where a product market monopolist is able to discriminate among consumers by applying a non-uniform price schedule that yields higher profits than otherwise. The discriminating monopoly theory implies that a seniority wage scale, usually accompanied by a '*last-in, first-out*' (LIFO) layoff rule, is adopted in the workplace.

Under this framework, workers are positioned according to their job tenure in a queue, a seniority rank, based on which they are hired and laid off. Therefore, the firm is bound to first employ the senior workers offering them a higher wage rate, before it can employ junior workers at their reservation wage. From the unions' point of view, irrespectively to what their preferences might be, concerning the distribution of rents among its members, a seniority wage scale can achieve greater employment efficiency and consequently more rents extracted from the firm (Kuhn 1988, Kuhn and Robert 1989). Firms, on the other hand, are likely to adopt such a policy for a variety of reasons. Based on a seniority wage scale policy, as outlined above, the marginal employment decision from the employers' perspective involves the low-wage junior workers who are employed only if their lifetime marginal product exceeds their lifetime income stream, both discounted at present value. Hence, as Booth and Frank (1996) claim, it is more profitable for the firm to hire at the bottom of a steep scale than the average wage on the scale would suggest. Furthermore, hiring costs are likely to exist and workers already employed may also have acquired firm-specific skills, i.e. outsiders are not perfect substitutes for insiders. Firms will attempt to discourage labour turnover among their most highly valued workers by implementing a seniority wage rule that under these circumstances appears to be an optimal policy. The adoption by firms of policies linking wages and tenure, of course, goes back to the 1970's, as it is a central element of the descriptive theory of internal labour markets (ILMs).

The concept of the ILM began with the seminal work of Doeringer and Piore (1971), who define the institution as "*an administrative unit within which the pricing and allocation of labour is governed by a set of rules and procedures*" (pp. 1). The reasons for the existence of such institutions lie in the characteristics of joint production and the problems of monitoring and consistent incentives. ILMs develop to deal with these problems in the face of specificity in human capital investments, and opportunistic behaviour in the context of information asymmetries.

The primary rationale for ILMs is usually supposed to be specific investment (Wachter and Wright, 1990). Skill specificity is measured by the skill's uniqueness to the job classification and the enterprise and is accumulated through on-the-job training. This kind of training occurs by '*osmosis*' in the production process (Doeringer and Piore, 1971), where the participants assume dual duties of learning and carrying out the tasks and "*is confined to those skills required for the job and no excess training*" (pp. 27). However, for the worker, increasing skill specificity "*reduces the incentive for him to invest in such training, while simultaneously increasing the incentive for the employer to make the investment*" (pp. 14), since the skills cannot be readily utilised elsewhere.

The four distinguishing features of ILMs, as summarised by Doeringer and Piore, are:

1. Entry to internal labour markets is via certain jobs and ports of entry.
2. Rules regarding job security, career arrangements and so on differentiate the insiders from the outsiders to the firms.
3. Employees are paid according to administrative rules and customs, so in a way wages are tied to jobs rather than to individuals. And,

4. Wages are influenced only weakly by conditions in the labor market external to the firm.

A cornerstone of the Doeringer and Piore characterisation of ILMs is the notion that wages are attached to jobs and to a lesser extent to individuals and their human capital. Thereby the firm commits itself to a reward structure, which relies on promotions. Access to higher level positions on internal promotion ladders is not open to all comers on an unrestricted basis. As part of the internal incentive system, higher level positions are filled by promotion from within whenever this is feasible. This practice, especially if it is adopted by other enterprises to which the worker might otherwise turn for upgrading opportunities, ties the interests of the worker to the firm in a continuing way. Given these ties the worker looks to internal promotion as the principal means of improving his position. Reliance on internal promotion has affirmative incentive properties in that workers can anticipate that differential talent and degree of cooperativeness will be rewarded. Consequently, although the attachment of wages to jobs rather than to individuals may result in an imperfect correspondence between wages and marginal productivity at parts of entry, productivity differentials will be recognised over time and a more perfect correspondence can be expected for higher level assignments in the internal labour market job hierarchy. Thus internal promotion ladders encourage a positive worker attitude towards on-the-job training and enable the firm to reward cooperative behaviour.

ILMs, therefore, consist of sets of careers and relatively detailed defined career paths that in turn lead to long-term attachments. Adopting an ILM strategy may raise firm's performance because career opportunities provide incentives to put forth more effort via promotion tournaments (Lazear and Rosen, 1981), delayed compensation (Lazear, 1981) or efficiency wages (Shapiro and Stiglitz, 1984) and to acquire firm-specific skills (Gibbons, 1997). Also, employers learn about their employees, which is useful in assigning workers to jobs and reduces firms' hiring and screening costs. An additional reason for the existence of ILMs is that they can provide valuable insurance and stability to employees (Bertrand, 1999). ILM agreements are commonly reached through collective bargaining. Unionisation commonly facilitates grievance procedures and contract revision and renewal that enable the adjustment of these agreements to the changing conditions and to unforeseeable contingencies in a relatively nonlitigious manner.

The discussion so far has clearly outlined unions' opposition to subjective pay mechanisms like the Performance-Related Pay (PRP) scheme and their preference over objective pay setting, the standardisation of wages and seniority policies. Trade unions, by enforcing such pay setting processes in the establishment, create a less competitive and quite secure environment for the covered workers. Individuals, especially those more '*vulnerable*' like seniors and minorities or female workers, feel more protected behind the egalitarian union representatives against layoffs and unfair or discriminating treatment. The standardisation of pay and the wage compression in the organised sector suggest that workers' true productivity and qualifications may not be appropriately acknowledged. In a Mincer wage equation model that would be interpreted into flatter returns to human capital compared to the non-union sector. The worker-friendly pay setting processes that unions advocate mean that workers are not rewarded according to their actual contribution and individual merit, but based on some objective rules. While this is beneficial for part of the workforce, individuals with high qualifications and competitive skills may feel restricted and unsatisfied in an environment like this. High-skilled workers who are willing to voice their concerns to management personally, or are able to find alternative employment relatively easily may not feel the need of representation. Therefore, while for some workers unionism may be regarded as a '*protective shield*', for some others it is more of a constraint, a burden in their career development. Effectively this may lead to a kind of sorting between the unionised and non-unionised sector based on individuals' need for protection and job security. Murphy *et al.* (1991), in their examination of the union effect on earnings distribution, conclude that "*one principal effect of the pursuit of standard rate policies by trade unions is the attraction of a more homogeneous workforce into union employment*" (pp. 536).

The aim of my study here is to explore how trade unions influence individuals' earnings profiles. In particular, I want to examine how unionism interacts with the human capital wage premia, when considered in a Mincer earnings equation framework. From the discussion above, I form two hypotheses that I wish to investigate. First, in workplaces with union representation, the returns to employer-tenure should be higher than in the non-union sector. The main rationales behind this argument are two. Employer-tenure measures the years an individual spent working for a particular employer, i.e. it is the seniority of an individual in a particular job. Since organised sectors are more likely to adopt seniority rules as their pay setting process, instead of PRP schemes, I expect that seniority earnings profiles will be steeper than in workplaces with no workers' associations. Furthermore, as Booth at al. (2001) suggest, relative to non-union workers, union-covered workers are more likely to receive training and they also receive more days of training than their non-unionised counterparts[37]. In addition, they experience higher wage growth and a greater return to training. We can anticipate then that workers in the unionised sector are more likely to accumulate firm-specific skills,

[37] A number of other studies on British data have found a positive correlation between work-related training incident and measures of union presence (Booth 1991; Greenhalgh and Mavrotas 1994; Arulampalam and Booth 1998; Green, Machin and Wilkinson 1999).

through training. Therefore, the returns to employer-tenure, as a proxy for job-specific skills, will be higher for the covered workers.

The second proposition is that the returns to more transferable type of skills, acquired in work and appreciated by a number of employers, are steeper in the less restrictive and more competitive non-union sector. Contrary to the traditional opposition of unions to any pay setting mechanism based on individual merit, managers at workplaces with no union representation are more friendly and supportive to PRP schemes. Concequently, in non-unionised establishments, workers are more likely to be rewarded based on their actual skills and productivity. Hence, true qualifications and competitive skills should be more important in these jobs than in unionised workplaces.

Booth and Frank (1996) in a recent study on British data propose that union wage differential increase with seniority but only when formal seniority scales exist[38]. In the same spirit, Theodossiou (1996) argues that tenure has a significant positive effect on earnings in jobs with promotion policies, although he does not make any distinction between unionised and non-unionised firms. Nevertheless, this finding is in support of our first proportion since, as the analysis outlined before, the standardisation of pay setting procedures and promotion policies are strongly guarded by unions' '*sword of justice*'. In this chapter, there are many similarities with the study of Booth and Frank (1996), however the innovation of this work is that it provides a more detailed and complete map of the acquired human capital that has some rather interesting implications concerning the individuals' earnings

[38] In the US literature, Topel (1991) argues that the returns to tenure for union members are larger in magnitude and rising compared to their non-union peers, while Kuhn and Sweetman (1999) looking from a different perspective find that the loss to displaced workers from unionised workplaces is increasing in seniority.

profiles. While the previous studies divide accumulated human capital into firm-specific and general labour market, based on the analysis in ***Chapter 3***, I argue that acquired skills in work should be further decomposed. The existing literature overlooks the importance of occupation-specific skills in the wage determination process.

Here I adopt this approach and alongside job-tenure and labour market experience I include occupational and industry experience in my analysis. Job-tenure is usually considered in the literature as a measure of seniority and, under the assumption that workers accumulate firm-specific human capital, as a proxy of non-transferable (between jobs) skills. On the other hand, we can think of occupational experience as a measure of the individual's expertise in a particular occupation, i.e. of the individual's occupation-specific skills that are transferable between different firms/employers within the same job description (occupation). It is of great interest to explore how trade unions and/or formal wage policies in a workplace affect the individuals' earnings profiles when examined at the different levels of transferability of the accumulated skills. According to Booth and Frank (1996) seniority wage scale policies are more likely to be adopted in workplaces where strong trade unions are present and individual productivity is hard to measure. If we imagine such a workplace we would probably expect job tenure, rather than true productivity, to play an important role on earnings. On the contrary, in a more competitive environment, not so restricted by formal wage policies, one might expect that the individual's expertise on the job she performs and consequently her productivity would be more appreciated and rewarded. In this chapter I address these questions and explore how workplace features, like unionism and seniority scales, influence the importance of job-tenure and accumulated skills in the wage determination process.

In the next section, I examine the interaction between union representation in the workplace and individuals' earnings profiles. I begin my analysis with the estimation of standard union and non-union wage equations, *Section 4.2.1*, and in the second part, *Section 4.2.2*, I address the selectivity issue in the estimates, driven by the endogeneity of union status. In *Section 4.3*, I explore whether we can explain the observed distinct earnings paths in union and non-union jobs with the existence of formal seniority wage policies in these workplaces. Finally in *Section 4.4*, I conclude my discussion with a summary of the most important findings.

4.2 Seniority Earnings Profile Under Unionism

The purpose of this section is to examine the different wage growth paths in the union and non-union sector. Before I address though this question, I need to decide on the definition of union status. I can define union status either at the individual level as union membership, or at the workplace level as union coverage. The choice between the two is actually the answer to whether there is a free-rider problem associated with union membership or not. One of the main roles of trade unions is the improvement of wages and working conditions above the perfectly competitive level (the union's monopoly role). Economists, Olson (1965) among the first, have argued that there is indeed a free-rider problem associated with union wage premium. The reason behind that is that in an establishment, where a union is recognised for pay bargaining, all workers regardless of their membership status can enjoy the improved wages and working conditions. Therefore, the above the perfectly competitive level wages and the better working conditions are normally a collective good since it is difficult to exclude workers who are not union members. Individuals acting as rational economic agents faced with a public good are expected to take a free ride on union membership and enjoy this collective good without incurring the monetary or physic costs of membership. Two recent studies

(Booth and Bryan, 2001; Bryson, 2002) using the linked employer-employee data from the Workplace Employee Relations Survey 1998 (WERS) provide empirical evidence to the free-rider argument. The authors examine the membership premium among covered workers and conclude that there was no union membership wage premium in the late 1990s for Britain's private sector workers[39].

The question that naturally comes to mind is why then individuals still want to join a union or, why union members do not leave the union. Trade unions are also traditionally associated with the provision of friendly society benefits, grievance procedures and the like. These are normally excludable, private goods or services available only to union members that may act as an incentive to workers to unionise (Booth and Chaterji, 1995). In addition, workers may feel the need or pressure to comply with the group norm of union membership (Booth, 1985; Naylor, 1989) or they may join and remain members because they are ideologically committed to doing so. The theoretical rationale and empirical evidence, in conclusion, suggests that the union wage premium is a public good available to all covered workers regardless of membership status. Therefore, in my analysis here I define union status solely based on the existence of a recognised trade union in the workplace. This way I may optimally avoid the *'free-rider'* effect in a union job, which applies to a considerable proportion of workers in United Kingdom.

The empirical examination is based on the same unbalanced panel sample used in *Chapter 3*. Some of the main characteristics of this sample are provided in *Table A.4.1*, where averages on employer-tenure, general total labour market experience, industry and occupational experience are presented separately for the union and

[39] Similarly, Barth *et al.* (2000) using a matched emloyer-employee data set for Norway find that individual membership status ceases to have any significant effect on the wage when establishment-level union density is included and conclude that the union wage effect is a pure public good.

non-union sector. Although an analysis on simple descriptive statistics would probably be inadequate and certainly not exhaustive, the figures in the table are quite indicative of some distinct patterns that govern these two sectors. In particular, what is interesting here is the fact that in general the average duration of employment history, measured either as tenure or experience, is longer in the organized sector than in the non-union sector. A finding that probably reflects the higher job stability and security that former workplaces actually offer. The most characteristic example from the table is male employees' recorded tenure, where on average men in unionised jobs appear to stay with their current employer about two years more, compared with their peers in the non-union sector.

The discussion in this section focuses on the workers' earnings profiles in the union and non-union sector. In the first part (*Section 4.2.1*), I present conventional wage equation estimates separately for a workplace with union representation and without. Then in the second part (*Section 4.2.2*), I concentrate on the issue of the endogeneity of union status, and re-estimate these earnings models, controlling for potential selectivity bias in the results.

4.2.1 Unionism and Wage Equations

I begin the analysis here by estimating standard Mincer earnings equations separately for the union and the non-union sectors:

$$W_{uit} = \beta_{u0} + \beta_{u1} X_{uit} + \varepsilon_{uit} \qquad (4.1)$$

$$W_{nit} = \beta_{n0} + \beta_{n1} X_{nit} + \varepsilon_{nit} \qquad (4.2)$$

where W_{uit} is the log union wage and W_{nit} is the log nonunion wage for individual i at period t. X is the vector of variables determining earnings and β's are the coefficients to be estimated. The dependent variable is the logarithm of the hourly wage rate, including overtime paid hours. The human capital variables on the right-hand side of the equation include job-tenure (measured in decades), actual labour market experience, industry and occupational experience (measured in years)[40]. Alongside these variables, the remaining regressors consist of controls for individual characteristics such as education, skills, qualification and current occupation, workplace characteristics like establishment size and industry sector and regional dummies and a time trend. The results are summarised in ***Tables 4.1*** and ***4.2***, for the male and female employees, where the derived ten-year effect[41] of tenure, labour market experience and industry and occupation experience is calculated and presented, in order to help the comparison between these two sectors. I acknowledge that the estimates of the effect of these four variables may be inconsistent due to unobserved heterogeneity across individuals and across matches. Although this potential endogeneity bias is not of major concern, I utilise the panel element of our data set and employ panel estimators[42], generalised least square (GLS) and within-group fixed effects (FE)[43], alongside OLS estimator. Finally, on

---

[40] Quadratic polynomial for labour market experience and cubic polynomials for the other three human capital variables.

[41] Through out the chapter, I present the findings from the estimated earnings model, based on the calculated ten-year effect of the four human-capital variables of interest.

[42] A technical note concerning the estimation process, for observation unit in the panel estimates I use alternatively (I) the individual, and (II) the individual working for a specific employer, i.e. if an individual is observed working for different employers in the sample she is treated as a different unit/individual. The latter method may capture some unobserved job-match effects that the former might not, especially for the estimates on the returns to job-tenure.

[43] When fixed effect estimators are employed, an identification problem arises driven by the presence of both employer-tenure and actual labour market experience in the wage equation model. For those individuals who do not have any part-time employment spell, the increase between two consecutive waves in both tenure and labour market experience is the same. This implies that I cannot simultaneously estimate their effect when using fixed effects (difference from mean). The only case

what it concerns the level of identification of the industry and occupation sector for the measurement of the individual's accumulated experience in them, I use alternatively both the 1-digit and 2-digit level of classification.

The results presented in ***Table 4.1*** provide a rather interesting insight on the differences in the earnings profiles between the union and non-union sector. If we compare the first half of the table (union) with the second half (non-union) we can derive some distinct paths between the two sectors. Job tenure, while it appears to have a modest but positive and significant contribution in those establishments where workers are organised into trade unions, the same is not true for their peers in the non-union sector. Furthermore, in the union sector labour market experience and occupational experience are estimated to have a significant positive effect on individuals' earnings. However the impact is stronger in the less restricted non-unionised workplaces. This is especially true for occupational experience, where the calculated contribution (ten-year effect) is at least double the size compared to the union sector. Finally, wages, in the second half of the table, appear to increase with industry experience, particularly when the latter is measured at the 2-digit level of classification. According to these findings, seniority and/or firm-specific skills are important only in workplaces with trade unions present. In work environments

---

where they can be both estimated is for those individuals who had some part-time working experience between, for example, two consecutive waves. In that case the increase in labour market experience will be higher than the one in employer-tenure. Effectively though that means that the obtained coefficients of labour market experience do not measure its effect on wages, but rather capture this event in their employment history. Therefore, when fixed effect estimators are employed, in order to avoid this kind of identification problem I exclude the linear term of labour market experience from the estimated model. Consequently, in the case of fixed effects the returns to labour market experience are not presented in the tables.

though less protective and restricted, it is the more competitive and transferable kind of human capital that really matters in the wage determination.

The estimates on ***Table 4.2*** do not provide a clear picture of the effect of union representation on the earnings profiles of female employees. First of all, in both sectors employer-tenure and industry experience do not appear to play any significant role in the wage determination. Total labour market experience and occupational expertise, on the other hand, are estimated to have a significant positive effect on wages, however there is no distinct pattern on their returns in the two sectors. Therefore, despite the variation in their magnitude, the evidence is not conclusive and I cannot make any comment, as I do for the male employees, on the interaction between unionism and these estimated wage premia.

Overall though, this first attempt to explore the earnings profiles in the covered and non-covered sector sheds some light. From the wage equation models on the male employees I can conclude that seniority is closely related to wages in workplaces where trade unions exist. In these protected working environments where formal policies probably exist concerning the employment and the level of wages, senior workers are more valued compared with their junior colleagues. However, individuals with competitive and transferable skills, such as occupation-specific skills, are far better of in jobs less restricted where their true productivity is more likely to be acknowledged. On the contrary, the findings on the female workers are open to interpretation and are not so insightful at the current stage.

One main source of concern with the above findings is the endogeneity of union status. Individuals are not randomly assigned in the union or non-union sector. On the contrary, the distribution of workers among these two sectors is governed by rational decisions and behaviours of both the employees and the employers.

Workers select themselves into their most preferred sector, while employers choose from the pool of available workers those individuals that they desire. An obvious issue that arise from this discussion is the potential sample selection bias in the previous estimates. The two samples, in the union and non-union sector, may be characterised by different features concerning both the individuals and the workplace. In other words, the estimated differences in the wage equation models between the two sectors may after all be the result of the likely heterogeneity of the two samples, rather than genuine distinct patterns in the earnings profiles. I explore this route in the following section and address the selectivity issue in the wage equation framework.

4.2.2 Endogeneity of Union Status

It is generally agreed that union status should be treated as an endogenous variable (Dungan and Leigh 1985). The fact that, for example, we observe an individual in the union sector is the result of distinct systematically made decisions from the two parties involved (employees and employers), where they both aim to maximise their utility. A theoretical model, mainly developed in the US literature, that describes this whole process is the '*queuing model*' based on the influential and pioneer work of Abowd and Farber (1982) that basically involves a dual selection process. Workers, based on the utilities that each sector yields to them, make explicit decisions regarding their desire for union representation in their workplace. However, the preference towards the union sector does not necessarily result into employment on a union job, since it is the employer who decides whom to employ from the available queue of workers, in order to produce at minimum cost. Hence, "*a worker's union status is determined by both a desire for a union job and the employer's selection criteria*" (pp. 355). In other words, the observable event of union status requires the queuing process from the employee's side and her being selected by the employer.

Although such a theoretical model may be quite insightful on the behaviours that govern the observable event of union status, it is still questionable whether it is applicable to the British labour market or not. Furthermore, since the only event the researcher observes is the union status is quite difficult to distinguish these two steps (queuing and selection) and discern whether non-union workers did not actually desire to work in a union job, or were just not chosen from the queue, although they wanted union representation. In practice that means that unless we can find at least one variable that is contained in one model (e.g. queuing) but not in the other (e.g. selection) we are unable to distinguish these two processes and identify the possible different behaviour patterns that characterise them. Therefore, due to the ambiguous validity of the model for the case of Britain and to limitations in my data set, I do not pursuit this route. Instead I estimate a probit model on the event of union status that although it does not provide us with any insight on both employees and the employers' decisions, it still serves well its purpose concerning the control of selectivity bias.

Specifically, I estimate the structural form of the union status model, specified as:

$$Union^{*}_{ij} = \alpha_0 + \alpha Z_{it} + \varepsilon_{it} \qquad (4.3)$$

and

$$Union_{it} = 1 \text{ if } Union^{*}_{it} > 0 \text{ and } =0 \text{ otherwise}$$

where $Union^{*}_{it}$ is the latent variable indicating union representation in the workplace, $Union_{it}$ is the observed union status, Z_{it} is a vector of personal and job characteristics and $\varepsilon_{it} \sim \left(0, \sigma^2\right)$.

The regressors Z_{it} included in the union probit model are those used in the earnings equation model presented above. However, for identification purposes we require at least one more variable that affects the event of working in a job with union representation that has no obvious impact on wages. The author suggests that individuals' political beliefs may influence ones decision of whether or not to work in an unionised environment but they do not have any effect on their earnings profile. We can think of ideology as a proxy of what the views and perceptions of an individual are concerning various aspects of everyday life, including trade unions and collective bargaining in the workplace. Under this assumption, we would expect people located in the center and left at the '*political map*' to be friendlier towards the idea of unionism and collective action[44]. ***Figures 4.1*** and *4.2* give us a vague idea on how individuals, according to the party they support, are distributed between the union and non-union sector. Although one might argue that this is a rather traditional view, questioning its validity in nowadays, the empirical findings presented below support our initial assumption. Hence, alongside the regressors from the wage equation model I include three dummy variables corresponding to whether the individual feels closer to the Conservative party, Labour party or the Liberal Democrats[45]. BHPS contains a series of questions on respondents' political

---

[44] Arabsheibani and Marin (2001) use similar identifying variables for the construction of a structural union-membership equation in a selectivity-corrected union wage gap model for UK. Commenting on the validity of their choice, the authors argue that "*in the U.K. trade unions have always been closely associated with the Labour Party in particular, and with more left wing policies in general*" (pp. 2).

[45] The methodology employed here relies on the conventional assumption that individuals' political views and party attachment are rather stable in the long term (Green and Palmquist, 1990). Therefore, while short-term factors (e.g. economic conditions) may influence voters, such shifts are transitory, as individuals are expected rather soon to return to their preferred party. Within this

views. In particular, individuals are asked if they support a particular political party, and if so which party they regard themselves as being closer to than the others. The replies to these two questions form the basis for the construction of the political beliefs dummy variables that I use below.

Tables 4.3 and *4.4* present the derived marginal effects from the estimated union status probit model. The model is estimated both at 1-digit and 2-digit of industry and occupational classification, however the results remain fairly similar irrespectively to the chosen level of identification. Before we move on to the findings, it should be stretched out that the interpretation of the results is not a straightforward one. The difficulty arises from the fact that the actual process of joining a union job is unobserved to the researcher. Therefore, I reckon that it would probably be more appropriate to interpret the findings as the effect that individual and job characteristics have on the probability that one is observed in a unionised workplace, rather than attempt to suggest behavioural strategies from the employers and employees. Starting with the findings on the male sample, in general the signs on the significant variables in the union status equation are what would be expected *a priori*.

The polynomial terms of job tenure appear to be significant, suggesting a positive relationship between seniority and union status. One possible interpretation of this finding is that the individuals who plan to stay for many years in a job and accumulate tenure are more likely to be observed in a workplace with union representation. Apparently, the security that trade unions offer provides an incentive to those individuals who seek stability in their careers. On what it

---

framework, political beliefs are formed at an early life stage based on parents' given preferences, socio-economic status, race, religion and region and remain fairly stable over the years.

concerns the political beliefs, the individual used as the base for the estimates is he who supports a party different from the three most popular mentioned above or, no party at all[46]. According to the findings, the workers who support the Labour party are those most likely to be observed in an unionised environment, followed by the Liberal Democrat supporters. Those located to the right in the political spectrum are less likely to work in the unionised sector, compared to the supporters of the other two major parties. Furthermore, the results suggest some strong regional effects especially for the North and the Wales, where the probability that an individual is employed in a union job are higher compared to the reference region of the South. In addition, the model captures some industry and occupation effects on the probability of union status suggesting that some sectors are more likely to have union representation than others, or simply that workers in particular sectors prefer more to work in a unionised place. More specifically, individuals in *Agriculture*, *Energy* and *Manufacture of Metals, Mineral Products and Chemicals* sector as well as *Other Services* are more likely to work in an unionised environment. While those in *Metal Goods* and *Engineering* industries and in *Hotels* and *Catering* sector are the least likely to be represented by a trade union. Moreover, those with *Managerial* and *Professional* occupations have lower probability of being observed in an unionised workplace compared with employees in other occupations. According to the estimates, the occurrence of union status is more likely in larger workplaces, which is something that we should expect since union representation in general is more likely to be observed in workplaces with a large number of employees. Two last remarks on the findings, semi and high skilled workers, as well as non-manual workers are those that are most likely to be working in a union job. And finally, the probability of union status reduces as the years pass. Whether though this occurs

[46] The base group, those who support a party other than the three main ones or does not support any, is approximately one quarter of the whole sample, in the case of male employees. While, for the female respondents it rises up to one third.

because unionism overall declines through the years or simply because of some unobserved time trend captured in the data is not clear.

Before we move on to the findings on the female employees, there is an issue that worthies addressing here. The estimates on the union-status probit model in ***Table 4.3*** suggest a positive relationship between union-status and job seniority. One interpretation that I suggest above is that individuals who prefer stability to possibly frequent job changes are more likely to find employment in an unionised environment. However, there may be an alternative explanation to this estimated effect. Employer-tenure may be endogenously determined by some unobserved individual and workplace characteristics that may also influence whether an individual is employed in a unionised sector or not. Similarly to a wage equation model, the estimated positive effect of tenure may actually be driven by the correlation with individual and workplace characteristics not observed to the researcher. Here I attempt to clarify this issue and take a closer look on the potential endogeneity of the obtained job-tenure effect.

A test of endogeneity always requires the specification of a list of instruments for the variables under suspicion. For that purpose of my analysis I employ the instrumental variables suggested by Altonji and Shakotko (1987) (AS thereafter), where employer-tenure is instrumented by the deviation from its job-match mean for every individual. On the basis of this instrument I compute a test of exogeneity for the union-status probit model as proposed by Smith and Blundel (1986). This test is related to the Davidson-MacKinnon auxiliary regression test for exogeneity in a regression context (an alternative to the commonly used Hausman test). This test involves a two-step estimation process. In the first stage, the variables suspected for endogeneity are expressed as a linear projection of a set of instruments, those specified by the researcher plus all other explanatory variables of the probit model.

The residuals from each first stage instrument regression are then included in the probit model. A test on the joint significance of the coefficients on the residual series is performed. Under the null hypothesis, the probit model is appropriately specified with all suspected variables as exogenous, i.e. the residuals from the auxiliary regressions should have no explanatory power. A rejection of the null hypothesis indicates that the standard probit estimator should not be employed. The performed Smith-Blundel test of exogeneity, based on the AS instrumented variables for tenure, rejects the null hypothesis with a *Chi-square* ($X^2_{(3)}$) of 10.936 (*Chi-square*: 11.809, when industry and occupational experience are measured at a 2-digit level). Employer-tenure appears to be endogenously determined in the union-status probit model. After all, the unobserved individual and workplace characteristics that affect the presence of an individual in an unionised workplace appear to influence also the duration of his employment spell in that job.

As an alternative model to the union-status probit model in ***Table 4.3***, I can employ the instrumental variable probit model using Amemiya Generalised Least Squares (AGLS)[47] that is used for estimating probit models where some of the independent variables are endogenous (in our case the employer-tenure polynomial). The estimates from this IV-Probit model on union-status (not included here) reduce the estimated effect of tenure both in magnitude and in statistical significance. Seniority does not appear to have an explanatory role anymore in the event of been employed in a union-sector. The findings from the IV-Probit on the rest of the regressors remain fairly similar to those provided in ***Table 4.3***. Apparently, what this analysis implies is that the previously estimated positive relationship between union-status and job-tenure may actually have to do with the fact that tenure is endogenously

[47] Maddala (1983) provides a good summary of how AGLS works and Newey (1987, eq. 5.6) the specific formulas used for the estimation.

determined in this probit model[48]. Nevertheless, for the estimation purposes of Heckman's selection model on the earnings equations I employ the probit model presented in ***Table 4.3***.

The estimates on the female employees in ***Table 4.4*** are fairly similar to those already discussed with only a few differences observed. First of all, only the linear terms of the polynomials of job tenure and labour market experience are positive and significant, while all the terms of the industry experience are significant at the 1-digit of classification and only the first term at the 2-digit level. Nevertheless, job tenure still has a positive effect on the probability of being observed in a union job, like in the case of male workers[49]. Furthermore, employees' qualifications appear now to affect the probability of union status, where previously in the case of male workers they are (apart from a few exceptions) insignificant. Employees with teaching qualifications are those most likely to be working in union jobs compared to all other individuals with different qualifications. Probably this is something one might expect if we assume that these individuals are working in relevant sector (education) where union representation in the workplace is quite common.

Moving now in my analysis, if union status is endogenous in a wage equation framework, then:

$$E(\varepsilon_{uit} \mid Union_{it}^{*} > 0) \neq 0 \text{ and } E(\varepsilon_{nit} \mid Union_{it}^{*} \leq 0) \neq 0$$

This means that OLS estimated coefficients of the wage ***Equations (4.1)*** and ***(4.2)*** are inconsistent. In ***Tables 4.5*** and ***4.6*** I present the estimated earnings equations, where

[48] I should acknowledge though that my discussion here relies on the specific instruments used and consequently on how appropriate and valid they are for the sample.

[49]The Smith-Blundel test is performed here as well in order to test the exogeneity of employer-tenure. The estimated Chi-square suggests that the probit model is the one that should be employed, since the null hypothesis (exogeneity) is not rejected.

I control for selectivity, based on the union status probit models discussed above. The Heckman maximum-likelihood estimates overall deliver rather similar estimates to those summarised in ***Tables 4.1*** and *4.2*, where I do not control for potential sample selection bias. According to the results on the male employees, job tenure has a positive and significant effect only in the union sector. Apparently, seniority is an important determinant of individuals' earnings profiles in a workplace with union representation[50]. A finding that verifies my discussion above on the role of trade unions on the remuneration policies adopted by the management and their positive attitude towards the standardization of wages and seniority policies. On the other hand, total labour market experience appears to have a contribution of similar magnitude on both sectors. Occupational experience, although, is appreciated and rewarded in both sectors, the magnitude of its effect on wages differs between them, with the non-union sector being more appreciative to it. The derived returns to ten years of occupational expertise in the, more competitive and less structured, non-union sector are more than triple in size compared to the well protected working environment of a union job. Finally, the results suggest that selectivity is significant only in the non-union sector. The positive sign of *rho* at the bottom of the table for the non-union sector simply indicates that the factors, which have a positive effect

[50] The selectivity-corrected model presented here does not consider the fact that employer-tenure may be endogenously determined in the union-status probit model. This may cast some doubt on the reliability of the estimated tenure effect in the former model. However, a performed Hausman test on the exogeneity of tenure in a wage equation model (as the one presented in *Table 4.1*) on the whole sample of male employees and separately on the union and non-union sub-samples, based on the AS instruments, is in favour of the OLS estimator (estimates not included here). Therefore, although the duration of the current employment appears to be simultaneously determined with the union-status, it behaves as an exogenous explanatory variable in the wage determination process, both in the union and non-union sector. This finding may reinforce our confidence on the derived estimates on seniority.

on the individual's earnings in the non-union sector also, raise the probability of being observed in this sector.

The findings in ***Table 4.6*** on the female employees are rather similar to those presented in the previous section, when using OLS. From the four variables of interest, representing seniority and accumulated skills in work, only total labour market experience and occupational experience are estimated to have a positive and significant effect. Their contribution appears to be higher in the non-union sector, however the difference is not as notable as it is for the male employees. Hence, based on the present results I cannot support any argument similar to the one discussed above for the male workers. Finally, there appears to be negative selectivity in the union sector, which implies that the individual and workplace characteristics that raise wages have an inverse effect on the probability of observing this individual in a union job.

The discussion presented here sheds some light to the different earnings paths followed in the union and non-union sector. At least for the male workers, the results strongly suggest that seniority plays an important role in the earnings profiles of those working in a workplace with union representation. On the contrary, in the more competitive and meritocratic environment of a non-union job, individuals appear to be rewarded for their true productivity and expertise. In the next session, I explore whether this phenomenon has to do merely with the presence of a trade union or with the existence of formal wage scale policies in that sector and what happens if no such policies are adopted in the union sector.

4.3 Pay-Rise Policies and Human Capital Wage Premia

My findings in ***Section 4.2*** imply the presence of distinct seniority-wages profiles between the union and non-union sector. Here, I attempt to provide a better understanding of the underlining mechanism in the unionised workplaces that drives these strong seniority-earnings ties. Trade unions are traditionally associated with the standardisation of pay-setting procedures and the adaptation of seniority rules in the workplace. In the previous section I examine whether union wage differentials increase with seniority without though making any distinction about the presence of pay-rise rules. The observed, at least for the male employees, steeper seniority profiles may universally be true for the whole covered sector, as the findings above suggest or, they may actually be driven by formal objective rules related to pay-setting that unions through bargaining enforce in the workplace. If the latter is true, then what happens in those establishments with union representation but no formal seniority policies? Are senior workers less protected in this case? These are the issues that I address in this section and attempt to shed some light on.

There are two candidate questions from BHPS that can help us identify workplaces where formal wage policies are adopted. Individuals are asked whether seniority wage scales exist in the current job[51]. In addition, there is another question, more general though, on the promotion opportunities in their current job[52]. The author is in favour of the former because it appears to be more directly linked to wages than the latter, which is broader in the sense that it may refer to aspects of work not

[51] The question addressed is: "*Some people can normally expect their pay to rise every year by moving to the next point on the scale, as well as receiving negotiated pay rises. Are you paid on this type of incremental scale?*".

[52] "*In your current job do you have opportunities for promotion?*".

related to earnings such as the job description, responsibilities and work conditions. From the 2834 male workers who reported that they have opportunities for promotion, only 1485 were expecting a pay-rise next year. Similarly, no more than 1221 from the 1772 female employees with promotion prospects in their current job responded that every year they were anticipating a wage increase. Therefore, I base my analysis on the information that individuals provide in BHPS concerning the existence of formal wage scale policies.

At the first part of this section, I present estimates on wage equations, similar to the ones in the previous section[53], where I divide and examine separately the workers depending on the existence of incremental wage scale policies in their current job. *Table 4.7* summarises the estimated effects in jobs with pay-rise and no pay-rise for the male workers. Employer-tenure does not appear to have an important role here in these estimates. The only case where I derive a significant and positive effect is when pay-rise policies are adopted, based on the OLS estimator. Total labour market experience has a strong positive effect on both cases, workplaces with or without seniority policies, but its effect is marginally stronger in the latter case. Furthermore, industry experience appears to have a significant and positive contribution only when measured at the more detailed 2-digit level of industry classification and in workplaces with pay-rise rules. The evidence also suggests that the more competitive and transferable occupation-specific skills are highly rewarded in the less restricted and more flexible workplaces where no formal seniority-wage scales exist. Analogously, the estimates on the female employees in *Table 4.8* suggest that industry experience has a more significant positive impact on wages in jobs with pay-rise policies. Occupational experience, antithetically, plays a far more

[53] The sample size marginally reduces for both male and female employees, due to missing information on the existence of wage scales in their current job.

important role in the more competitive environment of a workplace where wages are not governed by formal seniority policies. The findings overall imply that there are obvious similarities between the earnings profiles in a union job and in a job with seniority-wage scales. I continue my analysis towards that direction and I first explore which are the individual and job characteristics that determine the existence of scale coverage in a workplace.

The probit estimates of the determinants of scales coverage are given in ***Tables 4.9*** and ***4.10*** for the male and female workers, respectively. The two main findings that stand out from ***Table 4.9*** are the strong union effect and the role of firm size in the adoption of wage scale policies. Workplaces with trade unions present are more likely to have seniority wage scale rules. According to the estimated marginal effect of union job, union representation increases the probability of adopting a seniority-wage rule by 20 per cent, a rather significant effect. The '*discriminating monopoly*' view, discussed above, provides the theoretical reasoning why trade unions may relate wages to seniority through formal scales. It worthies noting that in these estimated models I consider only the presence of a trade union in the workplace and not the individual membership. In an alternative specification (results not presented here) I include union membership in the regressors vector. The interesting result that comes out of this model is that whether an individual is a member of a trade union or not does not appear to have any notable effect on the probability of getting a pay-rise next year. What this finding really implies is that adopted seniority-earnings policies, probably as the outcome of a bargaining process between the management and union representatives, apply to all covered workers in the establishment, regardless of their membership status. More explicitly, wage incremental policies are public goods, not excludable to workers who did not join the trade union. Antithetically, when I estimate a similar probit model on the probability of getting a promotion the following year (the other candidate variable, available in BHPS) I find that union membership increases significantly the chances of being promoted (estimates excluded from the analysis). The estimated positive and significant effect of union membership in the latter model clearly suggests that promotions when negotiated by a trade union are more of a private good, available mainly to union members. This is a quite interesting finding which in a way provides further support and reasoning to my initial choice of pay-rise policies instead of promotions as proxies of pecuniary future prospects of individuals' current employment. As mentioned earlier in the chapter, recent studies provide evidence of the *'free-rider'* phenomenon in unionised workplaces. Therefore since the improvement of wages is normally a collective good available to all workers in the union sector, we would expect that individuals could benefit from policies related to their wages without necessarily having to join a trade union. And, that is exactly what I find from these estimated probit models.

Continuing now to the remaining of ***Table 4.9***, we observe that as the size of the workplace increases, so does the probability of implementing a formal wage policy. This is something that one should expect, since seniority wage scale is likely to emerge as an alternative to individual performance related or merit pay in work-environments where productivity and output are difficult to monitor. This is especially true for firms with many employees, where due to the large scales of production it is inherently hard to measure productivity. Individuals who are already employed in a job, which requires substantial total labour market experience or industry experience, have a higher probability of operating under a pay-rise policy, compared with other colleagues. Occupational expertise, on the other hand, has a positive effect on wage scale rules, especially at the early stages of skills-accumulation (this is true only at the 1-digit level of occupation classification though). Finally, workers in *Agriculture*, *Energy* and *Manufacture of Metals*, *Mineral Products* and *Chemicals* and *Other Services* industries are significantly more likely to be covered by wage scales.

The estimates from ***Table 4.10*** on the female employees are on average quite similar to those on their male peers. Once again there is a strong positive union impact with a marginal effect of 28 per cent, and a positive relationship between firm size and the probability of wage scales, although the estimated marginal effects do not increase monotonically with the number of employees. Compared with the male estimates, we observe that there are some interesting occupational effects. Individuals in *Professional* or *Associate Professional* and *Technical* occupations are more likely to be covered by seniority-wages rules, compared with the *Managers* and *Administrators*, whereas those in *Personal* and *Protective Services* and *Sales* occupations are less likely to be covered by similar pay mechanisms.

Following Booth and Frank's (1996) analysis I re-estimate the pay-rise probit model, this time making a distinction between the union and non-union sector (estimates not included in the chapter). While Booth and Frank suggest that, in non-union jobs, scales do not affect earnings and the variables in their data set do not explain the existence of wage scales, my findings between the two sectors have some similarities. Many of the individual and job characteristics that play a significant role in union jobs appear to do so also in workplaces with no trade unions present. Therefore I cannot really distinguish any different pattern towards the implementation of wage policies in these two sectors.

Two main conclusions are drawn from the analysis so far. Seniority earnings profiles are quite distinct between jobs with wage scales policies and those with no such formal earnings rules. In addition, unionism has a strong positive effect on the probability of adopting a scale rule in the workplace. In the final part of this section, I investigate the earnings equations in the union and non-union sector, where I control for the existence of formal wage policies in these environments. The question I aim to answer here is whether the formal seniority policies, which are more likely to be adopted in a unionised workplace, are the reason behind the steeper seniority-earnings profiles we observe in the union sector. An issue of concern that arises from the estimates presented in *Tables 4.7* and *4.8*, as well as from the estimates presented below is the selectivity issue. The findings from the probit models on the existence of wage scales outlined the importance of various individual and workplace features on the adoption of such policies. The problem that the researcher faces in these cases is the selection of the appropriate controls that could serve for the identification of the selectivity variables in the earnings equations. In other words, we need to find some variables that influence the occurrence of a wage scale policy, but are not expected to have any direct impact on the wage determination process. Theodossiou (1996) suggests various controls on employees' social background and the employers' or employees' attitudes and characteristics, which can be included in the probit equation for the identification purpose. I explored this path, by examining various variables that optimally could serve this identification purpose, such as training provided by the employers and the presence of a second job. However, data limitations prevent me from finding such appropriate controls. Therefore, in the estimated earnings models presented below I do not correct for potential selectivity bias. Another possible source of sample selection is the fact that individual are not randomly assigned in union or non-union jobs. Following the analysis presented in *Section 4.2.2*, I similarly control for this union-driven sample selection bias in the discussion below.

Optimally, this selectivity correction may capture some of the possible former selection bias, since union jobs are more likely to implement a formal wage scale policy. In a way, when I identify the union selectivity variables in the estimated wage equation model, I may be incidentally doing so for the wage policy selectivity as well. The reason is that, as the union and wage scale probit models suggest, the individual and workplace characteristics that determine whether we observe a worker in a union job or not, are broadly the same that influence the allocation of the individual in a job with seniority scales or not. In what follows, I estimate a wage equation model on four sub-samples depending on whether there is union representation and formal wage scale policies in the workplace, separately for the male and female employees. I acknowledge the fact that I cannot *'entirely'* control the pay-rise selectivity issue and probably we should bear that in mind when investigating the findings presented below. However, when we make comparisons within the unionised sector between workplaces with and without formal seniority-wage rules, the selectivity issue probably is not very important. My intuition is that the individual characteristics and workplace features that determine the adoption of such rules in an establishment are likely to be present in both union sub-samples. After all, unionism, and consequently the determinants of union representation in a workplace, is one of the main explanatory variables in the estimated pay-rise probit model. The pay-rise selectivity issue may be more serious when we make comparisons between the union and non-union sector, where their main sample characteristics are likely to differ. If we control though for union-status sample selection we control for the differences in the two sub-samples (union and non-union). The differences that are also likely to influence the adoption of a formal wage rule in a workplace. Hence even in the case where we make comparisons between the two sectors it is not clear to the author how *'corruptive'* this potential pay-rise sample selection may eventually be.

Tables 4.11 and ***4.12*** summarise the main findings from the estimated earnings models. The first half of these tables corresponds to jobs with pay-rise policies and the other half to jobs with no such formal policy. Similarly, the first two columns refer to union jobs (1-digit and 2-digit of industry and occupation classification, respectively) while the other two to non-union ones. I present the derived ten-year effect of these four seniority and human capital variables of interest (with the standard errors in parentheses). Starting the discussion on the male workers, we observe some rather interesting patterns in the individuals' wage profiles. Employer-tenure is estimated to have a positive and significant effect of around 6 per cent (ten-year effect) on wages only for employees in workplaces with union representation and formal pay-rise policies (the most restricted workplace of all possible four). Antithetically, occupational expertise is appreciated only in the non-union sector, especially when no seniority rules are adopted (the least structured working environment). In addition, total labour market experience has a similar positive effect of around 15 per cent (ten-year effect) in both these two types of workplaces. These findings clearly provide support to the two propositions set earlier in the chapter. What we observe here is that while firm seniority and specificity are important in the most structured and well-protected and secure environments, occupational expertise and the more competitive kind of skills play a major role in the less restricted and more demanding workplaces. Generally though in the union sector, it is seniority, measured either by tenure or labour market experience, which has an important role in the wage determination process. Total labour market experience, although significant in both '*types*' of union jobs, it appears to play a more important role when no formal policies are adopted. The absence of formal wage rules does not mean that informal, unwritten rules do not exist in these workplaces. In fact, it is quite likely that even in these union jobs employers follow some kind of seniority rule concerning employment and wages. In jobs with no collective representation, apart from occupational expertise, labour market experience appears to have an important role on wages. It is interesting though to notice that the returns to labour market experience double in size (ten-year effect) when seniority scales are applied, an indication that seniority in general is quite important when wage scales are adopted. Overall, the findings suggest that there are different earnings profiles depending on seniority scales and union representation. Especially though within the non-union sector the diversity is more obvious, probably because in union jobs even if formal wage policies do not exist, some kind of unwritten seniority rules should govern employers' decisions.

The estimates from ***Table 4.12*** on the female employees, as previously in the chapter, do not provide a clear picture and are not as informative as similar estimates on male workers are. According to the findings, almost universally total labour market experience and occupational expertise are the variables, out of the four variables for accumulated human capital in work, that have an important role in the estimated wage equation models. General labour market experience, although significant in most cases, appears to be more appreciated in the non-union sector and especially when pay-rise policies are employed. Occupational expertise, on the other hand, has the highest estimated contribution in the union sector with no formal pay-setting procedures. Despite these observed differences though, I cannot identify any distinct pattern. The findings are not so insightful and do not provide sufficient evidence for my two propositions.

The main conclusion that I can draw from this discussion concerns only the male employees. The findings here imply that the existence of formal wage scales and union representation in a workplace has a significant influence on the seniority and human-capital earnings profiles. More specifically, seniority appears to be quite important in workplaces with formal wage scale policies both in the union and non-union sector. Furthermore, the estimates suggest that unionised jobs appreciate and reward seniority even when no pay-rise rules are adopted. A possible rationale is that in jobs with union representation even if no such formal policies exist, there probably are some unwritten seniority rules that govern employment and earnings determination. Non-union jobs with no incremental wage scales, on the other hand, are more responsive to workers' skills, expertise and true productivity.

4.4 Conclusion

In this chapter, I explore how institutional arrangements influence employees' wages. Particularly, the focus of this examination is to distinguish the different paths seniority-earnings profiles follow depending on whether the individual is employed in a workplace where trade unions and collective bargaining are present and/or where formal wage scale rules are adopted. Trade unions are traditionally associated with the standardisation of pay-setting procedures, the enforcement of objectives rules concerning promotions and wages in the workplace and are generally hostile to Performance-Related Pay and individual merit schemes. Within this framework, I set two propositions related to seniority profiles and union representation. In particular, I argue that in the union sector it is expected that job seniority and skills specificity will be an important determinant of wages, while in the less structured non-union sector true productivity, proxied by the more competitive accumulated skills and professional expertise, will have a key role on earnings profiles. Indeed my analysis on male employees verifies both propositions.

Estimating separate earnings equations for the union and non-union sector raises a selectivity issue of concern. Individuals are not randomly assigned in either sector, but it is rather the outcome of systematic decisions made by both the employer and the employees. Hence, the two observed sub-samples, the union and non-union sector, may be characterised by different individual and workplace features. Effectively then, the estimated differences in the wage equations between the two sectors may after all be the result of the likely heterogeneity in the two samples, rather than genuine distinct patterns in the earnings profiles. In other words, the endogeneity of union status can lead to inconsistently estimated returns to employer-tenure and the other human capital variables of interest. The issue of selectivity is therefore an important issue of concern and is specifically addressed in this chapter by employing the Heckman correction technique. In particular, my preferred wage equation estimator is the one based on the Heckman maximum likelihood estimator, which allows us to control for potential selection bias. The derived results from this estimator, summarised in ***Tables 4.5*** & ***4.11***, provide some rather interesting insights. Overall, it appears that senior workers, compared to their junior colleagues, are better off when covered by formal incremental scales, since seniority wage profiles are estimated to be steeper in these jobs. Furthermore, as the results suggest, formal wage rules are more likely to be adopted in workplaces with union representation. A theory that provides a rationale for this finding is the discriminating monopoly view discussed earlier in the chapter. In this framework, a multi-part pricing policy that takes the form of seniority wages is adopted in order to achieve greater total income for the trade union (monopolist) and reduce turnover and quits of the more valued, senior workers from the employer's point of view, in working environments where true productivity is difficult to measure. Nevertheless, there are indications that seniority plays a significant role even in union jobs with no such scales rules. One possible explanation, in the same spirit of this discussion, is that unwritten policies, which actually serve the same purposes as formal rules, are quite likely to be adopted in these union jobs. Occupational expertise, on the other hand, is highly rewarded in less restricted or structured environments, where individual productivity can be measured. The analysis implies that in jobs with no formal incremental scales, and especially in the non-union sector, employees' wages are determined by their competitive accumulated, occupational-specific skills rather than their seniority. In conclusion, workplaces with union representation and formal seniority earnings policies '*favour and protect*' their senior employees, while the more competitive non-union sector jobs are fairer in the sense that they reward the workers based on their true qualifications and output productivity. The evidence on female employees, on the other hand, is not conclusive and does not provide sufficient support to my two arguments. Nevertheless, I believe that the discussion here generates some interesting findings concerning workers earnings profiles and unionism in the British labour market of the 1990s. Trade unions, in this era of declining membership and representation power, still ensure either through formal policies, or unwritten rules a structured and well-protected environment for all covered workers.

Chapter 4: Tables

Table 4.1

Wage Equations & Unionism (Male Employees)										
	OLS		GLS(I)		GLS(II)		FE(I)		FE(II)	
	1-dgt	2-dgt	1-dgt	2-dgt	1-dgt	2-dgt	1-dgt	2-dgt	1-dgt	2-dgt
Union										
T10	.038	.038	.052	.047	.032	.028	.065	.057	.011	.003
	(.022)	(.023)	(.022)	(.022)	(.025)	(.026)	(.025)	(.025)	(.039)	(.039)
Exp10	.189	.202	.209	.218	.209	.218				
	(.022)	(.022)	(.031)	(.030)	(.031)	(.030)				
Ind10	.003	-.005	.004	.028	-.002	.014	.015	.044	-.004	.020
	(.023)	(.021)	(.021)	(.018)	(.022)	(.018)	(.023)	(.019)	(.024)	(.020)
Occ10	.045	.039	.050	.033	.042	.028	.035	.022	.021	.014
	(.021)	(.020)	(.018)	(.017)	(.018)	(.017)	(.019)	(.018)	(.020)	(.018)
Adj. R^2	.548	.547	.501	.498	.502	.500	.243	.243	.228	.228
Sample	2964									
Non-Union										
T10	.033	.016	-.003	-.001	.015	.009	-.011	-.002	.040	.040
	(.033)	(.033)	(.030)	(.030)	(.036)	(.036)	(.035)	(.035)	(.067)	(.067)
Exp10	.184	.201	.279	.300	.215	.232				
	(.033)	(.031)	(.041)	(.039)	(.041)	(.040)				
Ind10	.004	.060	.039	.041	.056	.056	.036	.029	.050	.043
	(.031)	(.029)	(.027)	(.022)	(.027)	(.023)	(.028)	(.023)	(.029)	(.024)
Occ10	.166	.124	.119	.074	.118	.087	.086	.042	.066	.049
	(.030)	(.029)	(.025)	(.024)	(.026)	(.024)	(.026)	(.024)	(.028)	(.025)
Adj. R^2	.551	.550	.484	.487	.494	.496	.276	.267	.224	.218
Sample	2063									

Notes: The estimated wage equation model includes: 3rd order polynomial in employer-tenure, industry and occupational experience and 2nd order polynomial in potential labour market experience, age left education, a time trend, plus dummy variables for region, industry and occupation, establishment size and individual's qualifications. Standard errors reported in brackets. In panel estimators (I), the observation unit is the individual. In panel estimators (II), the observation unit is the individual working for a particular employer. R^2 is defined as the within for the fixed-effects model and overall for the random-effects model.

Table 4.2

Wage Equations & Unionism (Female Employees)										
	OLS		GLS(I)		GLS(II)		FE(I)		FE(II)	
	1-dgt	2-dgt	1-dgt	2-dgt	1-dgt	2-dgt	1-dgt	2-dgt	1-dgt	2-dgt
Union										
T10	.013	.016	-.036	-.037	-.007	-.004	-.060	-.059	.003	.010
	(.026)	(.026)	(.025)	(.025)	(.030)	(.030)	(.030)	(.030)	(.058)	(.058)
Exp10	.073	.112	.165	.179	.138	.166				
	(.028)	(.025)	(.037)	(.033)	(.037)	(.033)				
Ind10	.028	.025	.022	.016	.032	.013	.044	.014	.051	.001
	(.028)	(.025)	(.027)	(.023)	(.028)	(.023)	(.031)	(.025)	(.032)	(.025)
Occ10	.149	.101	.060	.063	.058	.054	.032	.046	.030	.036
	(.024)	(.023)	(.021)	(.019)	(.021)	(.019)	(.023)	(.020)	(.023)	(.020)
Adj. R^2	.595	.589	.562	.557	.565	.559	.348	.347	.297	.296
Sample	2149									
Non-Union										
T10	-.075	-.062	-.009	-.015	-.038	-.042	.011	-.003	.033	.022
	(.041)	(.042)	(.036)	(.037)	(.045)	(.045)	(.041)	(.042)	(.077)	(.077)
Exp10	.106	.151	.141	.150	.132	.144				
	(.042)	(.037)	(.049)	(.046)	(.049)	(.046)				
Ind10	.029	.053	-.015	.034	-.001	.037	-.034	.026	-.023	.024
	(.042)	(.037)	(.031)	(.026)	(.032)	(.026)	(.033)	(.026)	(.034)	(.027)
Occ10	.191	.101	.091	.038	.093	.026	.048	.010	.046	-.006
	(.039)	(.036)	(.030)	(.024)	(.031)	(.024)	(.031)	(.025)	(.032)	(.025)
Adj. R^2	.538	.535	.474	.467	.484	.476	.292	.290	.269	.267
Sample	1438									

Notes: The estimated wage equation model includes: 3rd order polynomial in employer-tenure, industry and occupational experience and 2nd order polynomial in potential labour market experience, age left education, a time trend, plus dummy variables for region, industry and occupation, establishment size and individual's qualifications. Standard errors reported in brackets. In panel estimators (I), the observation unit is the individual. In panel estimators (II), the observation unit is the individual working for a particular employer. R^2 is defined as the within for the fixed-effects model and overall for the random-effects model.

Table 4.3

Union Status Probit Model (Male Employees)				
	1-digit		2-digit	
	dF/dx	z-stat.	dF/dx	z-stat.
Human Capital				
Ten/10	.298	4.22	.307	4.27
$(Ten/10)^2$	-.139	-2.50	-.153	-2.71
$(Ten/10)^3$	.022	1.91	.027	2.22
Exp	-.005	-1.43	-.005	-1.47
Exp^2	1.23e-04	1.52	1.33e-04	1.70
IndExp	.009	1.59	.001	0.20
$IndExp^2$	-2.70e-04	-0.71	5.20e-04	1.27
$IndExp^3$	2.27e-06	0.34	-1.53e-05	-2.05
Occexp	-.005	-0.84	.004	0.78
$Occexp^2$	3.66e-04	0.96	-3.79e-04	-0.96
$Occexp^3$	-8.04e-06	-1.18	6.28e-06	0.86
Leave	5.58e-04	0.15	-7.31e-05	-0.02
Region				
London	.018	0.59	.012	0.38
North	.087	4.01	.085	3.93
Midlands	.019	0.85	.017	0.79
Wales	.073	1.84	.074	1.85
Scotland	-.020	-0.61	-.016	-0.47
Political Beliefs				
Conservative	.045	2.08	.047	2.18
Labour	.157	7.83	.159	7.92
Liberal Dem.	.101	3.37	.107	3.56
Industry Sector				
SIC 2	-.345	-6.76	-.352	-6.89
SIC 3	-.406	-9.65	-.396	-9.38
SIC 4	-.297	-6.75	-.299	-6.80
SIC 5	-.201	-3.94	-.209	-4.11
SIC 6	-.419	-9.37	-.417	-9.32
SIC 7	.042	0.91	.036	0.79
SIC 8	-.256	-5.53	-.254	-5.50
SIC 9	.171	4.24	.171	4.24
Firm Size (ascending)				
Firm Size 2	.109	1.41	.108	1.40
Firm Size 3	.101	3.93	.097	3.78
Firm Size 4	.191	7.73	.187	7.58
Firm Size 5	.203	8.23	.199	8.09
Firm Size 6	.309	14.26	.309	14.25
Firm Size 7	.322	13.70	.321	13.65
Firm Size 8	.348	14.35	.349	14.41
Occupation				
SOC 2	.082	2.60	.085	2.70
SOC 3	.058	1.49	.066	1.68
SOC 4	.107	2.32	.110	2.39
SOC 5	.107	2.06	.109	2.11
SOC 6	.148	3.13	.144	3.04
SOC 7	.029	0.56	.039	0.77
SOC 8	.173	3.50	.176	3.59
SOC 9	.252	4.37	.256	4.46
Skills				
Semi-Skilled	.182	3.07	.179	3.03
High-Skilled	.189	2.98	.187	2.94
Foreman	.102	1.58	.101	1.56

(*Table 4.3 continued*).				
Non-Manual	.185	2.85	.183	2.82
Prmg	.042	0.58	.046	0.63
Qualifications				
High-Degree	.082	1.42	.089	1.57
First-Degree	-.030	-0.67	-.031	-0.70
Teaching Qual.	.090	1.34	.093	1.39
Higher Qual.	.043	1.50	.045	1.60
Nursing Qual.	.118	0.77	.137	0.89
A-Level	.117	3.74	.118	3.78
O-Level	.030	1.06	.034	1.21
Commql	-.086	-0.67	-.100	-0.78
CSE	-.010	-0.25	-.009	-0.21
Apprent	-.087	-1.68	-.091	-1.79
Other Qual.	.164	1.91	.168	1.97
Time Trend				
Wave	-.021	-5.45	-.021	-5.47
Pseudo R^2	.290		.291	
Sample	5027			

Notes: Derived marginal effects.

Table 4.4

Union Status Probit Model (Female Employees)				
	1-digit		2-digit	
	dF/dx	z-stat.	dF/dx	z-stat.
Human Capital				
Ten/10	.226	2.16	.242	2.28
$(Ten/10)^2$	-.095	-0.99	-.140	-1.45
$(Ten/10)^3$	.008	0.35	.017	0.72
Exp	.012	2.28	.008	1.67
Exp^2	-1.74e-04	-1.32	-1.46e-04	-1.24
IndExp	.016	1.78	.015	1.78
$IndExp^2$	-.001	-1.70	-3.73e-04	-0.54
$IndExp^3$	3.22e-05	2.47	7.68e-06	0.53
Occexp	-.011	-1.43	-.010	-1.09
$Occexp^2$	4.25e-04	0.72	-5.68e-05	-0.08
$Occexp^3$	-1.15e-05	-0.97	1.35e-05	0.79
Leave	.017	3.71	.013	2.93
Region				
London	-.044	-1.33	-.044	-1.33
North	.138	5.48	.136	5.40
Midlands	.063	2.24	.062	2.21
Wales	.126	2.81	.139	3.09
Scotland	.133	3.91	.128	3.75
Political Beliefs				
Conservative	.025	0.98	.027	1.06
Labour	.093	4.08	.100	4.37
Liberal Dem.	.105	3.18	.104	3.15
Industry Sector				
SIC 2	-.429	-4.37	-.435	-4.46
SIC 3	-.514	-6.37	-.478	-5.80
SIC 4	-.484	-5.79	-.465	-5.56
SIC 5	-.386	-2.53	-.373	-2.44
SIC 6	-.398	-4.95	-.362	-4.49
SIC 7	-.025	-0.28	-.009	0.10
SIC 8	-.350	-4.35	-.325	-4.04

(*Table 4.4 continued*).				
SIC 9	.086	1.13	.103	1.36
Firm Size (ascending)				
Firm Size 2	.146	1.43	.139	1.37
Firm Size 3	.024	0.81	.026	0.88
Firm Size 4	.101	3.42	.097	3.31
Firm Size 5	.187	6.23	.184	6.16
Firm Size 6	.193	6.86	.191	6.76
Firm Size 7	.297	9.54	.294	9.35
Firm Size 8	.379	13.77	.376	13.59
Occupation				
SOC 2	.109	2.44	.080	1.79
SOC 3	-.043	-0.87	-.085	-1.73
SOC 4	.001	0.02	-.101	-1.99
SOC 5	.233	2.89	.181	2.11
SOC 6	-.003	-0.05	-.050	-0.86
SOC 7	-.076	-1.09	-.101	-1.43
SOC 8	-.003	-0.04	-.044	-0.50
SOC 9	.210	2.39	.194	2.19
Skills				
Semi-Skilled	.240	2.48	.227	2.33
High-Skilled	.236	2.16	.224	2.04
Foreman	.050	0.41	.048	0.40
Non-Manual	.199	1.82	.185	1.71
Prmg	-.018	-0.16	-.042	-0.37
Qualifications				
High-Degree	.176	2.38	.155	2.08
First-Degree	.174	3.52	.134	2.68
Teaching Qual.	.232	4.31	.187	3.31
Higher Qual.	.184	5.00	.146	3.94
Nursing Qual.	.172	2.94	.132	2.20
A-Level	.247	6.64	.231	6.14
O-Level	.204	6.22	.170	5.19
Commql	.157	3.61	.127	2.88
CSE	.293	5.92	.270	5.16
Apprent	.251	1.79	.242	1.69
Other Qual.	-.013	-0.12	-.067	-0.57
Time Trend				
Wave	-.011	-2.37	-.011	-2.29
Pseudo R^2	.307		.304	
Sample	3587			

Notes: Derived marginal effects.

Table 4.5

Wages Equation Corrected for Selectivity (Male Employees)				
	Union		Non-Union	
	1-dgt	2-dgt	1-dgt	2-dgt
T10	.040	.040	-.025	-.051
	(.023)	(.024)	(.035)	(.036)
Exp10	.189	.202	.188	.205
	(.022)	(.022)	(.034)	(.032)
Ind10	.004	-.004	-.011	.053
	(.023)	(.021)	(.032)	(.030)
Occ10	.045	.039	.163	.114
	(.021)	(.020)	(.031)	(.030)
rho	.025	.035	.561	.613
	(.131)	(.130)	(.069)	(.059)
LR-test (X^2)	0.03	0.07	17.83	22.07
Log Likelihood	-2991.271	-2990.264	-3265.642	-3261.547
Sample	2964		2063	

Notes: The estimated wage equation model includes: 3rd order polynomial in employer-tenure, industry and occupational experience and 2nd order polynomial in potential labour market experience, age left education, a time trend, plus dummy variables for region, industry and occupation, establishment size and individual's qualifications. Standard errors reported in brackets.

Table 4.6

Wages Equation Corrected for Selectivity (Female Employees)				
	Union		Non-Union	
	1-dgt	2-dgt	1-dgt	2-dgt
T10	-.011	-7.95e-04	-.089	-.068
	(.026)	(.027)	(.041)	(.042)
Exp10	.058	.102	.093	.147
	(.028)	(.025)	(.042)	(.037)
Ind10	.016	.007	.022	.048
	(.028)	(.026)	(.041)	(.038)
Occ10	.163	.114	.198	.105
	(.025)	(.023)	(.038)	(.036)
rho	-.481	-.407	.206	.103
	(.087)	(.116)	(.140)	(.206)
LR-test (X^2)	8.93	4.81	1.50	0.16
Log Likelihood	-1848.061	-1875.004	-2187.664	-2202.476
Sample	2149		1438	

Notes: The estimated wage equation model includes: 3rd order polynomial in employer-tenure, industry and occupational experience and 2nd order polynomial in potential labour market experience, age left education, a time trend, plus dummy variables for region, industry and occupation, establishment size and individual's qualifications. Standard errors reported in brackets.

Table 4.7

Wage Equations & Seniority Scales (Male Employees)										
	OLS		GLS(I)		GLS(II)		FE(I)		FE(II)	
	1-dgt	2-dgt	1-dgt	2-dgt	1-dgt	2-dgt	1-dgt	2-dgt	1-dgt	2-dgt
Pay-Rise										
T10	.074	.070	.045	.030	.039	.027	.028	.013	-.018	-.021
	(.027)	(.027)	(.027)	(.027)	(.030)	(.030)	(.032)	(.032)	(.052)	(.052)
Exp10	.175	.189	.224	.227	.207	.211				
	(.026)	(.025)	(.033)	(.032)	(.034)	(.033)				
Ind10	.017	.048	.015	.053	.011	.048	.019	.050	.002	.033
	(.028)	(.026)	(.026)	(.022)	(.026)	(.022)	(.030)	(.024)	(.031)	(.025)
Occ10	.040	.011	.055	.047	.044	.038	.061	.060	.039	.041
	(.025)	(.025)	(.022)	(.021)	(.022)	(.021)	(.024)	(.023)	(.025)	(.024)
Adj. R^2	.542	.541	.507	.504	.510	.508	.248	.251	.227	.229
Sample	2233									
No Pay-Rise										
T10	.003	-.003	.018	.019	.010	.011	.044	.049	.027	.030
	(.026)	(.027)	(.025)	(.026)	(.029)	(.029)	(.030)	(.030)	(.054)	(.054)
Exp10	.199	.215	.238	.262	.214	.236				
	(.027)	(.026)	(.035)	(.033)	(.035)	(.034)				
Ind10	.016	.021	.023	.024	.034	.033	.033	.019	.028	.027
	(.026)	(.023)	(.022)	(.019)	(.023)	(.019)	(.024)	(.020)	(.025)	(.020)
Occ10	.121	.094	.095	.055	.093	.057	.051	.013	.031	.006
	(.024)	(.023)	(.021)	(.019)	(.021)	(.020)	(.022)	(.020)	(.023)	(.021)
Adj. R^2	.540	.539	.492	.491	.501	.500	.222	.218	.185	.183
Sample	2780									

Notes: The estimated wage equation model includes: 3rd order polynomial in employer-tenure, industry and occupational experience and 2nd order polynomial in potential labour market experience, age left education, a time trend, plus dummy variables for region, industry and occupation, establishment size and individual's qualifications. Standard errors reported in brackets. In panel estimators (I), the observation unit is the individual. In panel estimators (II), the observation unit is the individual working for a particular employer. R^2 is defined as the within for the fixed-effects model and overall for the random-effects model.

Table 4.8

Wage Equations & Seniority Scales (Female Employees)										
	OLS		GLS(I)		GLS(II)		FE(I)		FE(II)	
	1-dgt	2-dgt	1-dgt	2-dgt	1-dgt	2-dgt	1-dgt	2-dgt	1-dgt	2-dgt
Pay-Rise										
T10	.022	.028	-.004	-.012	-.019	.016	-.037	-.044	.030	.015
	(.026)	(.027)	(.025)	(.026)	(.031)	(.031)	(.031)	(.031)	(.057)	(.057)
Exp10	.120	.148	.171	.186	.153	.174				
	(.029)	(.026)	(.037)	(.034)	(.037)	(.034)				
Ind10	.090	.055	.087	.086	.097	.076	.069	.066	.069	.048
	(.031)	(.027)	(.028)	(.023)	(.029)	(.023)	(.032)	(.025)	(.035)	(.026)
Occ10	.114	.059	.046	.039	.036	.023	.032	.029	.013	.009
	(.026)	(.024)	(.022)	(.019)	(.023)	(.019)	(.024)	(.020)	(.026)	(.021)
Adj. R^2	.582	.578	.557	.552	.560	.556	.354	.356	.307	.309
Sample	2066									
No Pay-Rise										
T10	-.073	-.047	-.043	-.034	-.040	-.028	-.044	-.039	-.005	.012
	(.042)	(.043)	(.036)	(.036)	(.042)	(.042)	(.043)	(.043)	(.083)	(.084)
Exp10	.103	.141	.193	.198	.182	.191				
	(.039)	(.036)	(.048)	(.045)	(.048)	(.045)				
Ind10	.044	.055	-.023	-.011	-.010	-.005	-.043	-.027	-.024	-.021
	(.038)	(.035)	(.030)	(.026)	(.030)	(.026)	(.032)	(.026)	(.033)	(.027)
Occ10	.217	.120	.113	.057	.114	.047	.067	.030	.071	.018
	(.037)	(.034)	(.029)	(.025)	(.029)	(.024)	(.031)	(.026)	(.031)	(.025)
Adj. R^2	.547	.540	.499	.489	.502	.492	.269	.263	.250	.243
Sample	1510									

Notes: The estimated wage equation model includes: 3rd order polynomial in employer-tenure, industry and occupational experience and 2nd order polynomial in potential labour market experience, age left education, a time trend, plus dummy variables for region, industry and occupation, establishment size and individual's qualifications. Standard errors reported in brackets. In panel estimators (I), the observation unit is the individual. In panel estimators (II), the observation unit is the individual working for a particular employer. R^2 is defined as the within for the fixed-effects model and overall for the random-effects model.

Table 4.9

Pay-rise Probit Model (Male Employees)				
	1-digit		2-digit	
	dF/dx	z-stat.	dF/dx	z-stat.
Trade Unions				
Union	.201	11.29	.201	11.27
Human Capital				
Ten/10	.033	0.51	.068	1.05
$(Ten/10)^2$	-.014	-0.29	-.042	-0.88
$(Ten/10)^3$	.002	0.24	.008	0.83
Exp	-.012	-3.19	-.011	-3.20
Exp^2	1.45e-04	1.89	1.37e-04	1.85
IndExp	-.017	-2.89	-.020	-3.52
$IndExp^2$	.001	3.66	.001	3.53
$IndExp^3$	2.61e-05	-3.87	-2.59e-05	-3.38
Occexp	.012	2.22	.007	1.22
$Occexp^2$	-9.12e-04	-2.44	-3.67e-04	-.092
$Occexp^3$	1.56e-05	2.31	4.80e-06	0.64
Leave	-.007	-1.89	-.006	-1.67
Region				
London	-.012	-0.40	-.007	-0.26
North	-.074	-3.59	-.079	-3.83
Midlands	-.068	-3.20	-.068	-3.24
Wales	-.057	-1.51	-.062	-1.65
Scotland	-.034	-1.13	-.038	-1.24
Industry Sector				
SIC 2	-.099	-2.17	-.099	-2.17
SIC 3	-.203	-5.52	-.201	-5.48
SIC 4	-.144	-3.77	-.140	-3.68
SIC 5	-.073	-1.57	-.077	-1.67
SIC 6	-.122	-3.02	-.128	-3.15
SIC 7	-.171	-4.32	-.174	-4.40
SIC 8	-.192	-4.83	-.197	-4.98
SIC 9	.049	1.28	.047	1.24
Firm Size (ascending)				
Firm Size 2	.043	0.51	.042	0.49
Firm Size 3	.031	1.15	.029	1.09
Firm Size 4	.077	2.88	.078	2.92
Firm Size 5	.071	2.60	.070	2.57
Firm Size 6	.116	4.57	.117	4.59
Firm Size 7	.148	4.91	.151	5.01
Firm Size 8	.183	6.27	.183	6.28
Occupation				
SOC 2	.174	5.47	.158	4.93
SOC 3	.064	1.66	.052	1.34
SOC 4	.005	0.12	-.015	-0.33
SOC 5	-.055	-1.05	-.072	-1.39
SOC 6	.003	0.07	-.006	-0.13
SOC 7	-.005	-0.10	-.018	-0.36
SOC 8	-.053	-1.02	-.074	-1.45
SOC 9	.037	0.60	.021	0.34
Skills				
Semi-Skilled	.079	1.38	.089	1.55
High-Skilled	.080	1.28	.078	1.24
Foreman	.077	1.24	.076	1.23
Non-Manual	.135	2.10	.137	2.15
Prmg	.043	0.62	.048	0.69

(*Table 4.9 continued*).				
Qualifications				
High-Degree	-.186	-3.52	-.201	-3.84
First-Degree	-.062	-1.53	-.070	-1.72
Teaching Qual.	.006	0.10	.012	0.20
Higher Qual.	-.026	-0.97	-.029	-1.07
Nursing Qual.	.101	0.69	.120	0.82
A-Level	-.021	-0.68	-.026	-0.83
O-Level	-.048	-1.78	-.049	-1.79
Commql	-.025	-0.23	-.028	-0.25
CSE	-.155	-4.15	-.154	-4.13
Apprent	.066	1.29	.063	1.24
Other Qual.	.045	0.56	.047	0.59
Time Trend				
Wave	-.021	-5.94	-.020	-5.70
Pseudo R^2	.133		.132	
Sample	5013			

Notes: Derived marginal effects.

Table 4.10

	Pay-rise Probit Model (Female Employees)			
	1-digit		2-digit	
	dF/dx	z-stat.	dF/dx	z-stat.
Trade Unions				
Union	.277	12.68	.278	12.77
Human Capital				
Ten/10	-.081	-0.79	-.051	-0.48
$(\text{Ten}/10)^2$	-.021	-0.23	-.051	-0.53
$(\text{Ten}/10)^3$	.010	0.42	.017	0.73
Exp	-.001	-0.24	-.004	-0.75
Exp^2	1.72e-05	0.13	7.13e-05	0.62
IndExp	-.004	-0.46	-.015	-1.79
IndExp^2	2.60e-04	0.52	.001	1.95
IndExp^3	-5.77e-06	-0.62	-2.70e-05	-1.96
Occexp	-.024	-3.07	-.014	-1.63
Occexp^2	.001	2.50	8.68e-04	1.24
Occexp^3	-2.29e-05	-2.10	-1.84e-05	-1.20
Leave	-.003	-0.79	-.004	-0.96
Region				
London	-.015	-0.45	-.013	-0.42
North	.055	2.18	.052	2.07
Midlands	-.047	-1.64	-.047	-1.63
Wales	.002	0.04	-1.98e-04	0.00
Scotland	.023	.066	.024	0.70
Industry Sector				
SIC 2	-.289	-2.87	-.294	-2.93
SIC 3	-.325	-3.72	-.326	-3.72
SIC 4	-.332	-3.81	-.341	-3.93
SIC 5	-.198	-1.37	-.223	-1.55
SIC 6	-.209	-2.47	-.216	-2.56
SIC 7	-.203	-2.15	-.195	-2.07
SIC 8	-.124	-1.47	-.120	-1.42
SIC 9	-.022	-0.27	-.024	-0.30
Firm Size (ascending)				
Firm Size 2	.119	0.98	.111	0.91
Firm Size 3	.092	3.14	.095	3.27

(*Table 4.10 continued*).				
Firm Size 4	.140	4.72	.140	4.72
Firm Size 5	.017	0.52	.017	0.51
Firm Size 6	.073	2.37	.072	2.32
Firm Size 7	.065	1.68	.068	1.76
Firm Size 8	.187	5.63	.190	5.72
Occupation				
SOC 2	.102	2.31	.098	2.25
SOC 3	.039	0.84	.035	0.78
SOC 4	-.025	-0.48	-.052	-1.08
SOC 5	.185	2.11	.184	2.10
SOC 6	-.092	-1.62	-.102	-1.83
SOC 7	-.142	-2.10	-.151	-2.26
SOC 8	.127	1.54	.115	1.40
SOC 9	-.038	-0.41	-.053	-0.58
Skills				
Semi-Skilled	.260	2.62	.253	2.55
High-Skilled	.279	2.55	.279	2.57
Foreman	.336	3.74	.333	3.72
Non-Manual	.599	6.12	.598	6.15
Prmg	.450	4.93	.448	4.94
Qualifications				
High-Degree	-.070	-0.88	-.083	-1.04
First-Degree	-.043	-0.79	-.048	-0.90
Teaching Qual.	.053	0.87	.052	0.84
Higher Qual.	.013	0.32	.013	0.33
Nursing Qual.	-.069	-1.08	-.077	-1.22
A-Level	.007	0.17	.010	0.23
O-Level	.012	0.33	.013	0.36
Commql	.071	1.55	.075	1.66
CSE	-.170	-2.20	-.173	-2.23
Apprent	-.016	-0.09	-.016	-0.09
Other Qual.	.046	0.43	.068	0.64
Time Trend				
Wave	-.004	-0.80	-.004	-0.84
Pseudo R^2	.202		.202	
Sample	3576			

Notes: Derived marginal effects.

Table 4.11

Earnings, Unionism & Seniority Scales (Male Employees)				
	Union		Non-Union	
	1-dgt	2-dgt	1-dgt	2-dgt
Pay-Rise				
T10	.059	.064	.083	.045
	(.029)	(.030)	(.064)	(.064)
Exp10	.135	.157	.310	.290
	(.029)	(.028)	(.063)	(.059)
Ind10	-4.67e-04	.002	.050	.143
	(.032)	(.029)	(.061)	(.057)
Occ10	.033	.025	.137	.073
	(.028)	(.027)	(.058)	(.056)
rho	.127	.102	.725	.726
	(.145)	(.152)	(.069)	(.072)
LR test (X^2)	0.57	0.35	12.87	11.78
Log Likelihood	-1180.436	-1193.836	-1032.258	-1033.139
Sample	1670		563	
No Pay-Rise				
T10	.004	.002	-.055	-.070
	(.035)	(.036)	(.042)	(.042)
Exp10	.247	.249	.141	.169
	(.036)	(.035)	(.041)	(.039)
Ind10	.011	.001	-.029	.010
	(.033)	(.031)	(.038)	(.035)
Occ10	.020	.011	.169	.119
	(.031)	(.029)	(.036)	(.036)
rho	-.139	-.131	.511	.573
	(.116)	(.116)	(.108)	(.089)
LR test (X^2)	1.26	1.13	6.32	8.49
Log Likelihood	-1585.464	-1576.395	-2007.323	-2001.608
Sample	1292		1488	

Notes: The estimated wage equation model includes: 3rd order polynomial in employer-tenure, industry and occupational experience and 2nd order polynomial in potential labour market experience, age left education, a time trend, plus dummy variables for region, industry and occupation, establishment size and individual's qualifications. Standard errors reported in brackets.

Table 4.12

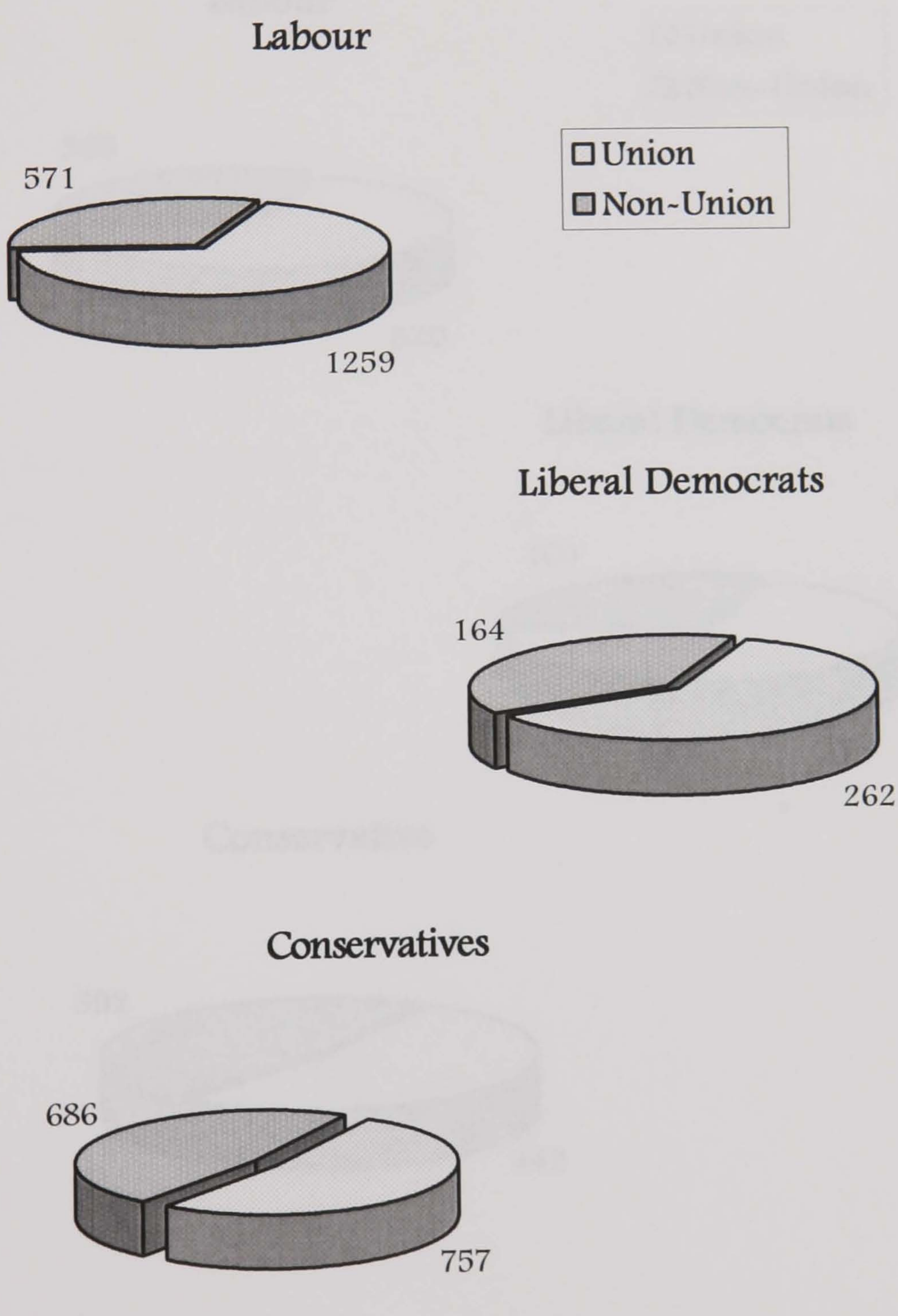
Earnings, Unionism & Seniority Scales (Female Employees)				
	Union		Non-Union	
	1-dgt	2-dgt	1-dgt	2-dgt
Pay-Rise				
T10	.003	.007	-.011	-.039
	(.029)	(.030)	(.064)	(.065)
Exp10	.040	.084	.222	.273
	(.033)	(.029)	(.068)	(.063)
Ind10	.068	.030	-4.42e-05	.043
	(.036)	(.031)	(.067)	(.061)
Occ10	.161	.106	.133	.035
	(.029)	(.027)	(.063)	(.056)
rho	-.717	-.715	.709	.695
	(.061)	(.061)	(.069)	(.074)
LR test (X^2)	18.04	20.94	16.86	14.55
Log Likelihood	-810.068	-820.608	-889.971	-891.345
Sample	1542		524	
No Pay-Rise				
T10	-.062	-.037	.005	.034
	(.064)	(.064)	(.060)	(.062)
Exp10	.139	.182	.166	.219
	(.060)	(.056)	(.059)	(.053)
Ind10	-.070	-.017	.102	.124
	(.061)	(.056)	(.059)	(.051)
Occ10	.239	.169	.221	.111
	(.050)	(.047)	(.055)	(.050)
rho	-.392	-.163	-.940	-.957
	(.194)	(.257)	(.018)	(.015)
LR test (X^2)	2.53	0.45	60.51	81.90
Log Likelihood	-753.549	-774.795	-980.031	-988.190
Sample	606		904	

Notes: The estimated wage equation model includes: 3rd order polynomial in employer-tenure, industry and occupational experience and 2nd order polynomial in potential labour market experience, age left education, a time trend, plus dummy variables for region, industry and occupation, establishment size and individual's qualifications. Standard errors reported in brackets.

Chapter 4: Figures

Figure 4.1

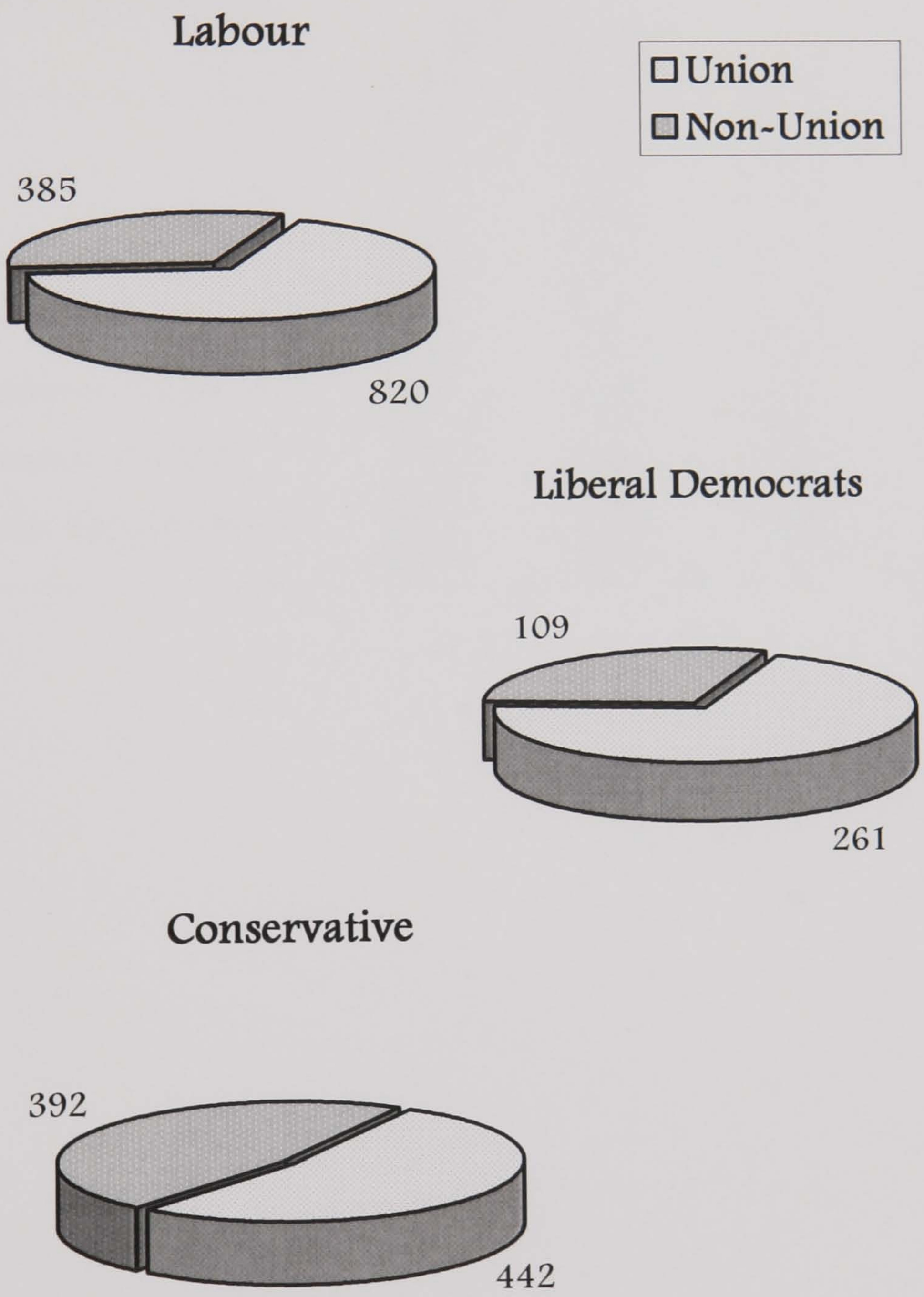
Political Beliefs and Unionism (Male Employees)†



†: Distribution of individuals between union and non-union jobs based on their political views.

Figure 4.2

Political Beliefs and Unionism (Female Employees)†



†: Distribution of individuals between union and non-union jobs based on their political views.

Chapter 4: Appendix

Table A.4.1

Sample Characteristics (BHPS): Waves 1-8				
	Male		Female	
No. of Individuals	985		734	
No. of Observations	5027		3587	
No. of Employees in a Union Job	2964		2149	
No. of Employees in a Non-Union Job	2063		1438	
	Mean (S.D.)		Mean (S.D.)	
	Union	Non-Union	Union	Non-Union
Age	40.40	38.92	39.41	39.19
	(9.69)	(9.88)	(9.78)	(10.55)
Employer Tenure	8.54	6.26	6.69	5.90
	(7.25)	(5.88)	(5.53)	(5.20)
Industry Experience (1-digit)	13.82	12.37	12.89	10.53
	(9.73)	(10.16)	(8.61)	(8.03)
Industry Experience (2-digit)	11.54	9.34	10.65	7.48
	(9.39)	(9.31)	(8.24)	(6.89)
Occupational Experience (1-digit)	12.05	10.32	11.58	10.58
	(9.90)	(9.75)	(8.85)	(8.87)
Occupational Experience (2-digit)	9.56	8.03	9.13	7.22
	(9.23)	(9.04)	(8.40)	(7.26)
Actual Labour Market Experience (full-time)	23.02	21.30	18.31	18.26
	(10.38)	(10.64)	(8.75)	(9.36)

Chapter 5

5 Conclusion to the Thesis

The significance of seniority for individuals' wage growth has been a very popular topic in labour economics for the past three decades. Despite though the volume of studies on this subject, it still remains a current issue with a lot of interest and appeal to both researchers and policy makers. The extent to which wages rise with employer-tenure is fundamental to the understanding of the dynamics of earnings and labour market behaviour. Estimates of tenure-wage profiles provide an insight into the evolution of earnings and can be informative on job mobility issues and issues related to the transferability of skills acquired in-work and individuals' employability. The importance of a study of seniority-earnings growth is further underlined by some of the features of the British labour market in the 1990s. The high labour turnover, the increased wage inequality and the persistence of low pay warrant an examination of wage determination and of how crucial job stability and seniority are for wage progression.

In *Chapter 2*, I examine the contribution of employer-tenure to earnings, while addressing the issue of potential heterogeneity bias in the estimates of interest, driven by possible correlation between unobserved individual and workplace characteristics and the duration of tenure. Particularly, individuals with high unobserved ability are expected to experience lengthy and less interrupted employment spells. Furthermore, high-paying jobs tend to last longer and have lower labour turnover. In spite of some variation in the estimated tenure effect across the different methods employed, most of the findings converge to the same conclusion. In the case of male full-time employees, tenure plays a limited role on earnings profiles. On average, the estimated ten-year contribution of tenure on log wages is slightly less than 10 per cent. The findings for the female sample are fairly similar, with ten years of employer-tenure having an effect of around 10 per cent. Further examination though of seniority-earnings profiles reveals that there is considerable heterogeneity in the contribution of tenure across the wage distribution, but only in the case of men. In particular, seniority is estimated to have a larger effect on those male employees located at the bottom of the wage distribution. The interpretation of this finding relies much on how one views the wage distribution. For example, we can assume that the distribution of wages reflects a distribution of different kind of jobs, with the low-paying jobs located at the lower quantiles of the distribution and the high-paying ones at the upper part of the distribution. Within this framework, one can argue that the estimates of the tenure effect suggest that seniority is far more important to those individuals in low-paying jobs compared with all other male workers. Nevertheless, irrespective of how we regard the wage distribution, the fact that employer-tenure has a larger contribution at the bottom of the wage distribution and only a modest effect at the mid and upper part of the distribution, has important wage-inequality implications. Apparently, seniority reduces wage inequality amongst male workforce. Thus, one force that could potentially drive men out of low pay and help them progress in the pay ladder is the accumulation of seniority in their current job.

Continuing the examination of the kind of acquired skills in work and their effect on individuals' earnings growth, in *Chapter 3* I depart from the common assumption that distinguishes obtained skills into employer specific and general labour market and explore the existence of industry and/or occupational specificity. The findings from the estimated wage equations are rather insightful on the human capital-earnings paths. Occupation specific skills appear to have a significant contribution to wages, highlighting the importance of expertise and specialisation in the British labour market of the 1990s. The evidence though on industry specificity is not strong and even in some cases inconclusive. However, a closer examination of these effects reveals that occupational and industry specificity matters mainly in high-paying, prestigious but demanding and competitive, at the same time, jobs, like *professional* and *managerial* jobs, or jobs in the *banking* and *finance* sector. The role of employer-tenure when industry and occupational experience are considered in the wage equations reduces. There is some evidence, only in the case of male employees though, that seniority and employer specific skills in mainly '*blue-collar*' jobs are important determinants of wages.

Trade unions are traditionally associated with the standardisation of pay-setting procedures and the enforcement of objectives rules concerning promotions and wages in the workplace. The British labour market though has gone through many changes since the late 1970s and the 1980s that resulted to declining unionisation and reduced trade union power. In *Chapter 4* I explore how union representation in the workplace interacts on the human capital wage premia, examined in the previous chapters. The findings on the male employees reveal that seniority-wage profiles are stepper in the union sector, compared with the non-union sector. In addition to that, formal wage rules are more likely to be adopted in workplaces where trade unions are present. Nevertheless, the evidence implies that even in unionised workplaces with no formal incremental rules, probably unwritten scale rules exist, since employer-tenure continues to be a significant determinant of wage growth. In the less restricted and more competitive non-union sector, the analysis indicates that occupational expertise is far more important than job seniority. Apparently, the non-unionised jobs are meritocratic, in the sense that they tend to reward the workers based on their true qualifications and output productivity. Whereas, the more structured union sector is more inclined to protect their senior workers and to provide job security and well-designed seniority-wage progression routes. The evidence on the female employees, in contrast, is not conclusive, thus we cannot draw similar conclusions as in the case of their male colleagues. Overall though, the findings from the analysis in this chapter suggest that trade unions in the 1990s, despite the declining membership and representation power, still yield the *'sword of justice'*, ensuring a well-protected environment to all covered workers.

The evidence from the three empirical chapters, as outlined above, provides some rather helpful insights on the patterns that govern individuals' wage growth and labour market behaviour that could prove to be valuable to policy makers on unemployment and wage inequality issues. Based on the estimated earnings equations at least on the male sample, there appear to be contrasting images. On the one side, there are the individuals with less skills and qualifications, usually employed in *'blue collar'* and low-paying jobs. For this part of the workforce, seniority and accumulated employer-specific skills appear to have a significant impact on their wage progression. In addition, this positive tenure-wages relationship is further strengthened when working in a structured environment with well-outlined promotion ladders and pay rules, like in the union sector. On the other end of the spectrum, there are those individuals with high educational qualifications mainly employed in demanding, but also high-paying and prestigious jobs. In their case, the accumulated, over the years, expertise in their occupation and industry sector is far more important in their wages growth than job seniority. Apparently, in these competitive working environments, it is true productivity, reflected in occupational and industry experience that employers reward. As probably one would expect this is particularly true in less restricted workplaces where there are no trade unions present and no seniority pay scales are adopted. Although, this description of the British labour market may be regarded as a rather simplistic view, the author believes that it is still indicative of the mechanisms that operate in the current labour market.

The British labour market in the 1990s is characterised by high labour market turnover, increased wage inequality and a larger number of atypical types of employment, like part-time and temporary jobs, who are mainly associated with low pay. Within this framework, a way, as the findings suggest, to reduce the wage inequality in the labour market is job stability for those at the bottom of the wage distribution. Since seniority for those workers is far more vital in their wage profiles compared with the rest of the workforce, policies that aim to reduce labour turnover and increase stability for this group of the workforce can prove to be quite effective. Concluding, this thesis attempts to shed some light on the different kind of skills individuals acquire in work and on the earnings profiles that characterise the workforce. Despite possible limitations this study may have, the author believes that the findings are of great interest and can be helpful and informative to policy makers in the evaluation of current labour market programmes, like the New Deal, and the design of the government's future agenda.

Bibliography

Abowd, J.M. and H.S. Farber (1982), "Job Queues and the Union Status of Workers", *Industrial and Labor Relations Review*, 35, 354-367.

Abraham, K. and H. Farber (1987a), "Job Duration, Seniority, and Earnings", *American Economic Review*, 77, 278-297.

Abraham, K. and H. Farber (1987b), "Returns to Seniority in Union and Nonunion Jobs: A New Look at the Evidence", NBER Working Paper No. 2368.

Abraham, K. and J. Medoff (1980), "Experience, Performance, and Earnings", *Quarterly Journal of Economics*, 94, 703-736.

Abraham, K. and J. Medoff (1981), "Are Those Paid More Really More Productive? The Case of Experience", *Journal of Human Resources*, 16, 186-216.

Addison, J.T. and P. Portugal (1989a), "Job Displacement, Relative Wage Changes, and Duration of Unemployment", *Journal of Labor Economics*, 7, 281-302.

Addison, J.T. and P. Portugal (1989b), "On the Costs of Worker Displacement: The Case of Dissipated Firm-Specific Training Investments", *Southern Economic Journal*, 56, 166-82.

Altonji, J.G. and R.A. Shakotko (1987), "Do Wages Rise with Job Seniority?", *Review of Economic Studies*, 54, 437-459.

Altonji, J.G. and N. Williams (1997), "Do Wages Rise with Job Seniority? A Reassessment", NBER Working Paper No. 6010.

Altonji, J.G. and N. Williams (1998), "The Effects of Labor Market Experience. Job Seniority, and Job Mobility on Wage Growth", *Research in Labor Economics*, 17. 233-276.

Arabsheibani, G.R. and A. Marin (2001), "Union Membership and the Union Wage Gap in the U.K.", The University of Wales, School of Management and Business, Research Paper 2001-5.

Arias, O., K.F. Hallock, and W. Sosa-Escudero (2001), "Individual Heterogeneity in the Returns to Schooling: Instrumental Variables Quantile Regression Using Twin Data", *Empirical Economics Journal*, 26, 7-40.

Arulampalam, W. (2001), "Is Unemployment Really Scaring? Effects of Unemployment Experiences on Wages", *Economic Journal*, 111, 585-606.

Arulampalam, W. and A.L. Booth (1998), "Labour Market Flexibility and Skills Acquisition: Is There a Trade-off?", *British Journal of Industrial Relations*, 36, 521-536.

Arulampalam, W., A.L. Booth and M. Taylor (2000), "Unemployment Persistence", *Oxford Economic Papers*, 52, 24-50.

Barth, E. (1997), "Firm-Specific Seniority and Wages", *Journal of Labor Economics*, 15, 495-506.

Barth, E., O. Raaum and R. Naylor (2000), "Union Wage Effects: Does Membership Matter?", *The Manchester School*, 86, 259-275.

Becker, G.S. (1962), "Investment in Human Capital: A Theoretical Analysis", *Journal of Political Economy*, 70, 9-49.

Becker, G.S. (1964), *Human Capital: A Theoretical and Empirical Analysis, with Special Reference to Education.* New York: Columbia Univ. Press (for NBER).

Becker, G.S. (1975), *Human Capital.* Chicago: University of Chicago Press.

Berger, C.J. and C.A. Olson (1982), "The Relationship Between Seniority, Ability, and the Promotion of Union and Nonunion Workers", in J. M. Douglas and D. B. Lipsky (eds), *Advances in Industrial and Labor Relations*, Greenwich, Conn.: JAI Press.

Bertrand M. (1999), "From the Invisible Handshake to the Invisible Hand? How Product Market Competition Changes the Employment Relationship", NBER Working Paper No. 6900.

Booth, A.L. (1985), "The FreeRider Problem and a Social Custom Model of Trade Union Membership", *Quarterly Journal of Economics*, 100, 253-261.

Booth, A.L. (1986), "Estimating the Probability of Trade Union Membership: A Study of Men and Women in Britain", *Economica*, 53, 41-61.

Booth, A.L. (1991), "What Do Unions Do Now? A Study of the Provision by British Trade Unions of Benefits and Services to their Members", *Labor Studies Journal*, 16, 50-64.

Booth, A.L. (1995), *The Economics of a Trade Union*. Cambridge: Cambridge University Press.

Booth, A.L. and M. Bryan (2001), "The Union Membership Wage Premium Puzzle: Is There a Free Rider Problem", CEPR Discussion Paper No. 2879.

Booth, A.L. and M. Chatterji (1995), "Union Membership and Wage Bargaining when Membership is not Compulsory", *The Economic Journal*, March, 345-360.

Booth, A.L., M. Francesconi and G. Zoega (2001), "Unions, Training, And Wages: Evidence For British Men", University of Essex, mimeo.

Booth, A.L. and J. Frank (1996), "Seniority, Earnings and Unions", *Economica*, 63, 673-686.

Booth, A.L., S.P. Jenkins and C.G. Serrano (1999), "New Men and New Women? A Comparison of Paid Work Propensities from a Panel Data Perspective", *Oxford Bulletin of Economics and Statistics*, 61, 167-197.

Brown, J.N. and A. Light (1992), "Interpreting Panel Data on Job Tenure", *Journal of Labor Economics*, 10, No 3, 363-396.

Bryson, A. (2002), "The Size of the Union Membership Wage Premium in Britain's Private Sector", PSI Discussion Paper No. 9.

Buchinsky, M. (1994), "Changes in the U.S. Wage Structure 1963-1987: Application of Quantile Regression", *Econometrica*, 62, 405-458.

Buchinsky, M. (1995), "Estimating the Asymptotic Covariance Matrix for Quantile Regression Models: A Monte Carlo Study", *Journal of Econometrics*, 68, 303-338.

Buchinsky, M. (1998), "Recent Advances in Quantile Regression Models: A Practical Guideline for Empirical Research", *Journal of Human Resources*, 33, 88-126.

Burgess, S. and H. Rees (1996), "Job Tenure in Britain, 1975-92", *Economic Journal*, 106, 334-344.

Campbell, N. (1999), "The Decline in Employment Among Older People in Britain", STICERD CASE Paper No.19.

Carmichael, L. (1983), "Firm Specific Human Capital and Promotion Ladders", *Bell Journal*, 14, 251-258.

Carrington, W.J. (1990), "Specific Human Capital and Worker Displacement", Diss. University of Chicago.

Carrington, W.J. (1993), "Wage Losses for Displaced Workers: Is It Really the Firm that Matters?", *Journal of Human Resources*, 28, 435-62.

Chamberlain, G. (1994), "Quantile Regression, Censoring, and the Structure of Wage", in C. Sims (ed), *Proceeding of the Sixth World Congress of the Econometric Society*, New York, Cambridge University Press.

Chay, K. and D. Lee (1996), "Changes in Relative Wages in the 1980s: Returns to Observed and Unobserved Skills and Black-White Wage Differentials", Princeton University Industrial Relations Section Working Paper No. 372.

Dickens, R. (2000), "Caught in a Trap? Wage Mobility in Great Britain: 1975-1994", *Economica*, 67, 477-497.

Dickens, R., P. Gregg and J. Wadsworth (2000), "New Labour and the Labour Market", CMPO Working paper Series No. 00/19.

Doeringer, P. and M. Piore (1971), *Internal Labor Markets and Manpower Analysis*. Heath, Lexington, Massachusetts.

Duncan, G.M. and D.E. Leigh (1985), "The Endogeneity of Union Status: An Empirical Test", *Journal of Labor Economics*, 3, 385-402.

Dustmann, C. and C. Meghir (1999), "Wages, Experience and Seniority", The Institute for Fiscal Studies, Working Paper Series.

Farber, H. (1983), "The Determination of the Union Status of Workers", *Econometrica*, 51, 1417-1438.

Frank, J. (1985), "Trade Union Efficiency and Overemployment with Seniority Wage Scales", *Economic Journal*, 95, 1021-1034.

Frank, J. and J. Malcomson (1994), "Trade Unions and Seniority Employment Rules", *European Economic Review*, 38, 1595-1611.

Freeman, S. (1977), "Wage Trends as Performance Displays Productivity: A Model and Application to Academic Early Retirement", *Bell Journal of Economics*, 8, 419-443.

Freeman, R. (1980), "The Exit-Voice Tradeoff in the Labor Market: Unionism, Job Tenure, Quits, and Separations", *Quarterly Economic Journal*, 94, 643-673.

Freeman, R. and J. Medoff (1984), *What do Unions do?*, New York: Basic Books.

Geweke, J. (1986), "Exact Inference in the Inequality Constrained Normal Linear Regression Model", *Journal of Applied Econometrics*, 1, 127-141.

Gibbons R. (1997), "Incentives and Careers in Organizations", in: D. Kreps and K. Wallis (eds), *Advances in Economic Theory and Econometrics*, London, Macmillan.

Gosling, A. and S. Machin (1995), "Trade Unions and the Dispersion of Earnings in British Establishments 1980-90", *Oxford Bulletin of Economics and Statistics*, 57, 167-184.

Gould, E.D. (2002), " Rising Wage Inequality, Comparative Advantage, and the Growing Importance of General Skills in the United States", *Journal of Labor Economics*, 20, 105-147.

Green, D.P. and B. Palmquist (1990), "Of Artifacts and Partisan Stability", *American Journal of Political Science*, 34, 872-902.

Green, F., S. Machin and D. Wilkinson (1999), "Trade Unions and Training Practices in British Workplaces", *Industrial and Labor Relations Review*, 52, 179-198.

Greenhalgh, C. and G. Mavrotas (1994), "The Role of Career Aspirations and Financial Constraints in Individual Access to Vocational Training.", *Oxford Economic Papers*, 46, 579-604.

Gregg, P. (2001), "The Impact of Youth Unemployment on Adult Unemployment in the NCDS", *Economic Journal*, 626-653.

Gregg, P., G. Knight, and J. Wadsworth (1999), "The Cost of Job Loss", in P. Gregg and J. Wadsworth (eds), *The State of Working Britain*, Manchester University Press.

Gregg, P. and J. Wadsworth (1995), "A Short History of labour Turnover, Job Tenure, and Job Security, 1975-93", *Oxford Review of Economic Policy*, 11, 73-90.

Gregg, P. and J. Wadsworth (1996), "Mind the Gap, Please? The Changing Nature of Entry Jobs in Britain", Centre of Economic Performance, LSE Discussion Paper 303.

Gregg, P. and J. Wadsworth (1999a), "Economic Inactivity", in P. Gregg and J. Wadsworth (eds), *The State of Working Britain*, Manchester University Press.

Gregg, P. and J. Wadsworth (1999b), "Job Tenure, 1975-98", in P. Gregg and J. Wadsworth (eds), *The State of Working Britain*, Manchester University Press.

Gregory, M. and R. Jukes (1997), "The Effects of Unemployment on Subsequent Earnings: A Study of British Men 1984-94", Centre for Economic Performance, Discussion Paper, University of Oxford.

Gregory, M. and R. Jukes (2001), "Unemployment and Subsequent Earnings: Estimating Scarring Among British Men 1984-94", *Economic Journal*, 111, 607-625.

Grossley, T.F., P.J. Kuhn, and M. Kukuk (1994), "Inferring Wage-Tenure Profiles from Displaced Worker Data", McMaster University, mimeo.

Guasch, J.L. and A. Weiss (1982), "An Equilibrium Analysis of Wage-Productivity Gaps", *The Review of Economic Studies*, 49, 485-498.

Harris, M. and B. Holmstrom (1982), "Ability, Performance, and Wage Differentials", *Review of Economic Studies*, 49, 315-333.

Hashimoto, M. (1981), "Firm-Specific Human Capital as a Shared Investment", *American Economic Review*, 71, 475-482.

Heckman, J.J. (1979), "Sample Selection Bias as a Specification Error", *Econometrica*, 47, 153-62.

Hirsch, B.T. and E.J. Schumacher (1998), "Unions, Wages, and Skills", *The Journal of Human Resources*, 33, 201-219.

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

Jackman, R. and S. Savouri (1999), "Has Britain Solved its Regional Unemployment Problem?", in P. Gregg and J. Wadsworth (eds), *The State of Working Britain*, Manchester University Press.

Jakubson, G. (1991), "Estimation and Testing of the Union Wage Effect Using Panel Data", *The Review of Economic Studies*, 58, 971-991.

Kim T.H., and C. Muller (2000), "Two-Stage Quantile Regression", University of Nottingham, Discussion Paper in Economics No. 00/1.

Kletzer, L.G. (1989), "Returns to Seniority After Permanent Job Loss", *American Economic Review*, 79, 536-43.

Kletzer, L.G. (1991), "Earnings after Job Displacement: Job Tenure, Industry, and Occupation", In J. T. Addison (ed), *Job Displacement: Consequences and Implications for Policy*. Chap. 4. Detroit, Mich.:State Universit Press.

Koenker, R. and G. Bassett (1978a), "Regression Quantiles", *Econometrica*, 46 (1), 1-26.

Koenker, R. and G. Bassett (1978b), "The Asymptotic Distribution of the Least Absolute Error Estimator", *Journal of the American Statistical Association*, 73, 618-622.

Koenker, R. and G. Bassett (1982), "Robust Tests for Heteroskedasticity Based on Reression Quantiles", *Econometrica*, 50 (1), 43-61.

Koenker, R, and S. Portnoy (1996), "Quantile Regression", Office of Research Working Paper No. 97-0100, College of Commerce and Business Adminitration, University of Illinois at Urbana-Champaign.

Kuhn, P. (1988), "A Nonuniform Pricing Model of Union Wages and Employment", *Journal of Political Economy*, 96, 473-508.

Kuhn, P. and J. Robert (1989), "Seniority and Distribution in a Two-Worker Trade Union", *Quarterly Journal of Economics*, 104, 485-505.

Kuhn, P. and A. Sweetman (1999), "Vulnerable Seniors: Unions, Tenure, and Wages following Permanent Job Loss", *Journal of Labor Economics*, 17, 671-693.

Lazear, E. (1981), "Agency, Earnings Profiles, Productivity, and Hours Restrictions", *American Economic Review*, 71, 606-620.

Lazear E. and S. Rosen (1981), "Rank-Order Tournaments as Optimum Labor Contracts", *Journal of Political Economy*, 89, 841-864.

Lefranc, A. (2001), "On the Sensitivity of Returns to Seniority to the Measurement of Earnings", THEMA, University of Cergy-Pontoise mimeo.

Machin, S. (1997), "The Decline of Labour Market Institutions and the Rise in Wage Inequality in Britain", *European Economic Review*, 41, 647-657.

Machin, S. (1999), "Wage Inequality in the 1970s, 1980s and 1990s", in P. Gregg and J. Wadsworth (eds), *The State of Working Britain*, Manchester University Press.

Machin, S. (2002), "Does It Still Pay to Be in a Union?", Centre for Economic Performance, Working Paper No.1180, LSE.

Maddala, G. (1983), *Limited-Dependent and Qualitative Variables in Econometrics.* Cambridge University Press.

Manning, A. (1998), "Mighty Good Thing: The Returns to Tenure", Centre for Economic Performance, Discussion Paper No.383, LSE.

Metcalf, D., K. Hansen and A. Charwood (2001), "Unions and the Sword of Justice: Unions and Pay Systems, Pay Inequality, Pay Discrimination and Low Pay", *National Institute Economic Review*, 176, 61-76.

Mincer, J. (1974), *Schooling, Experience and Earnings.* New York, NBER.

Murphy, K.M. and F. Welch (1992), "The Structure of Wages", *Quarterly Journal of Economics*, 7, 284-326.

Murphy, P.D., P.J. Sloane and D.H. Blackaby (1991), "The Effects of Trade Unions on the Distribution of Earnings: A Sample Selectivity Approach", *Oxford Bulletin of Economics and Statistics*, 52, 517-542.

Naylor, R. (1989), "Strikes, Free Riders and Social Customs", *Quarterly Journal of Economics*, 104, 771-786.

Neal, D. (1995), "Industry-Specific Human Capital: Evidence from Displaced Workers", *Journal of Labor Economics*, 13, 653-77.

Newey, W. (1987), "Simultaneous Estimation of Limited Dependent Variable Models with Endogenous Explanatory Variables", *Journal of Econometrics*, 36, 231-250.

Nickell, S. (1976), "Wages Structures and Quit Rates", *International Economic Review*, 17, 191-203.

Nickell, S. (1982), "The Determination of Occupational Success in Britain", *The Review of Economic Studies*, 49, 43-53.

Oi, W.Y. (1962), "Labor as a Quasi-Fixed Factor", *Journal of Political Economy*, 70, 538-555.

Ong, P.M. and J.R. Lawrence (1993), "The Unemployment Crisis in Aerospace", Graduate School of Architecture and Urban Planning. University of California, Los Angeles.

Ong, P.M. and D. Mar (1992), "Post-Layoff Earnings Among Semiconductor Workers", *Industrial and Labor Relations Review*, 45, 366-79.

Olson, M. Jr. (1965), *The Logic of Collective Action*. Cambridge Massachusetts: Harvard University Press.

Paglin, M. and A.M. Rufolo (1990), "Heterogeneous Human Capital, Occupational Choice, and Male-Female Earnings Differences", *Journal of Labor Economics*, 8, 123-144.

Parent, D. (2000), "Industry-Specific Capital and the Wage Profile: Evidence from the National Longitudinal Survey of Youth and the Panel Study of Income Dynamics", *Journal of Labor Economics*, 18, 306-323.

Parsons, D.O. (1972), "Specific Human Capital: An Application to Quit Rates and Layoff Rates", *Journal of Political Economy*, 80, 1120-1143.

Podgursky, M. and P. Swaim (1987), "Job Displacement and Earnings Loss: Evidence from the Displaced Worker Survey", *Industrial and Labor Relations Review*, 41, 17-29.

Polachek, S.W. (1981), "Occupational Self-Selection: A Human Capital Approach to Sex Differences in Occupational Structure", *The Review of Economics and Statistics*, 63, 60-69.

Powell, J. (1983), "The Asymptotic Normality of Two-Stage Least Absolute Deviations Estimators", *Econometrica*, 51, 1569-1575.

Powell, J. (1984), "Least Absolute Deviations Estimation for the Censored Regression Model", *Journal of Econometrics*, 25, 303-325.

Powell, J. (1986), "Censored Regression Quantiles", *Journal of Econometrics*, 32, 143-155.

Robertson, D. and J. Symons (1990), "The Occupational Choice of British Children", *The Economic Journal*, 100, 828-841.

Robinson, C. (1989), "The Joint Determination of Union Status and Union Wage Effects: Some Tests of Alternative Models", *The Journal of Political Economy*, 97, 639-667.

Robst, J. and J. VanGilder (2000), "Atrophy Rates in Male and Female Occupations", *Economic Letters*, 69, 407-413.

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

Salop, S.C. and J. Salop (1976), "Self-Selection and Turnover in the Labor Market", *Quarterly Journal of Economics*, 90, 619-628.

Schmidt, P. and R.P. Strauss (1975), "The Prediction of Occupation Using Multiple Logit Models", *International Economic Review*, 16, 471-486.

Shapiro C. and J. Stiglitz (1984), "Equilibrium Unemployment as a Worker Discipline Device", *American Economic Review*, 74, 433-444.

Shaw, K.L. (1984), "A Formulation of the Earnings Function Using the Concept of Occupational Investment", *The Journal of Human Resources*, 19, 319-340.

Sloane, P.J. and I. Theodossiou (1993), "Gender and Job Tenure Effects on Earnings", *Oxford Bulletin of Economics and Statistics*, 55, 421-437.

Smith, R.J. and R.W. Blundell (1986), "An Exogeneity Test for a Simultaneous Equation Tobit Model with an Application to Labor Supply", *Econometrica*, 54, 679-686.

Stewart M.B. (1995), "Union Wage Differentials in an Era of Declining Unionisation", *Oxford Bulletin of Economics and Statistics*, 57, 143-166.

Stewart, M.B. (1999), " Low pay in Britain", in P. Gregg and J. Wadsworth (eds), *The State of Working Britain*, Manchester University Press.

Stewart, M.B. and J. Swaffield (1999), "Low Pay Dynamics and Transition Probabilities", *Economica*, 66, 23-42.

Taylor, M.F. (ed) with J. Brice, N. Buck and E Prentice (1997), *British Household Panel Survey User Manual Volume A: Introduction, Technical Report and Appendices.* Colchester: University of Essex.

Theodossiou, I. (1996), "Promotions, Job Seniority, and Product Demand Effects on Earnings", *Oxford Economic Papers*, 48, 456-472.

Topel, R. (1991), "Specific Capital, Mobility, and Wages: Wages Rise with Job Seniority", *Journal of Political Economy*, 99, 145-175.

Wachter, M.L. and R.D. Wright (1990), "The Economics of Internal Labour Markets", *Industrial Relations*, 29, 240-262.

Webb, S., M. Kemp, and J. Millar (1996), "The Changing Face of Low Pay in Britain", *Policy Studies*, 17, 255-271.

Williams, N. (1991), "Reexamining the Wage, Tenure and Experience Relationship", *Review of Economics and Statistics*, 73, 512-517.

Williamson, O.E., M.L. Wachter and J.E. Harris (1975), "Understanding the Employment Relation: The Analysis of Idiosyncratic Exchange", *Bell Journal of Economics*, 6, 250-278.