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Empirical Studies of Earnings Over the Life Cycle in Great Britain

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ABSTRACT

Since its formalisation, the theory of human capital has become the dominant model for explaining earnings over the life cycle. This framework hypothesises that individuals devote a certain proportion of their time in each year to acquiring productivity enhancing skills, which increases their earnings capacity in the labour market. Career breaks are one reason for why female workers are observed to earn less than males since during the break, no new investment is undertaken and the stock of existing skills depreciates. If these career breaks are planned, however, women will choose to invest in less human capital in all periods prior to the break occurring. The first part of the thesis specifically tests the prediction that future spells of non participation lower the quantity of human capital that women invest in during their early years. A model is developed predicting that women anticipating future career breaks invest in less schooling and enter the labour market with lower starting salaries than similarly able men. This negative effect on investment increases with the length of the break and the earlier the date at which the break begins. Using data from the National Child Development Study (NCDS), it is found that even after allowing for the possible simultaneous determination of non participation and schooling, women who experience career breaks by the age of 33 are observed as having invested in less full time education. In addition, women who experience any kind of break by age 33 earn, on average, 10% less than men in their first job. Due to the reduced form nature of the equation estimated, however, the direct effect that schooling has on earnings is not identified. This is addressed in a second statistical analysis using the NCDS, which relates earnings at age 33 to years of schooling. Unlike the conventional Mincerian earnings equation, however, separate estimates of the return to schooling are obtained for each of the local education authorities (LEAs) in England and Wales. These LEA-specific returns are then regressed on a set of variables capturing school quality in order to test the hypothesis that individuals receiving higher quality education earn a higher rate of return to schooling. The results suggest that although there exists considerable variation in the value of education across LEAs, school quality exerts little impact on these estimated rates of return.

Following the schooling phase of the life cycle, human capital theory predicts that workers continue to invest in new skills while employed within a job. Each year of labour market experience is then hypothesised to positively influence earnings. The existence of positive returns to experience may not, however, entirely reflect the benefits from past investments in human capital. Theories of job mobility are capable of predicting positive returns to experience independently of human capital accumulation. In the final part of the thesis, data from the British Household Panel Survey is used to estimate the effect that switching jobs has on the path of earnings over time. The results indicate that, over a three year period, the wage gain associated with mobility is approximately 10%. For males, it is found that one quarter of this gain is due to a once and for all increase in earnings at the point of job change and the remaining three quarters being attributable to moving into a job with a higher rate of growth of earnings. For females, these two wage effects contribute equally to the total mobility gain.

FACULTY OF SOCIAL SCIENCES

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Doctor of Philosophy

EMPIRICAL STUDIES OF EARNINGS OVER THE LIFE CYCLE IN GREAT BRITAIN

by David Michael Campbell

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The research undertaken within the thesis utilises two main sources of data- the National Child Development Study (NCDS) and the British Household Panel Survey (BHPS). Both the NCDS and BHPS data were made available through the ESRC Data Archive. The NCDS data were originally produced by City University Social Statistics Research Unit. The BHPS data were originally collected by the ESRC Research Centre on Micro-Social Change at the University of Essex, now incorporated within the Institute for Social and Economic Research. Neither the original collectors of the data nor the Archive bear any responsibility for the analyses or interpretations presented here.

Chapter 1 Introduction

The factors determining earnings has always been a central topic of discussion within economics. Writing in the eighteenth century, Adam Smith (1776) first discussed many of the potential explanations for observed wage differentials between individuals which are still held by labour economists today. Of particular importance was Smith's observation that some workers receive higher earnings as a reward for obtaining certain productivity enhancing skills that are not possessed by others. This is one of the earliest references to the theory of human capital, which is now widely believed to be one of the most important determinants of individuals' lifetime earnings. In addition, Smith also noted that individuals employed in jobs with less desirable characteristics would receive higher earnings than similarly skilled workers in more attractive jobs. This wage premium serves to equalise the value of all jobs in terms of both their monetary and non monetary components. The subsequent refinement of Smith's ideas into the theories of human capital and compensating wage differentials remain crucial in explaining the distribution of earnings across workers within a perfectly competitive framework. It is the theory of human capital accumulation, however, that has received the most attention from labour economists and has subsequently been adopted as the dominant model for the determination of earnings over the life cycle.

The human capital approach was formalised in the early work of Becker (1962, 1975), and Mincer (1958, 1962, 1974). Essentially, the approach developed in their work views the acquisition of productivity enhancing skills as an investment decision, where firms and workers calculate the costs and benefits of obtaining new skills. The worker benefits from such investments if it raises their productivity within the current job, which in turn, increases their potential earnings capacity. The main costs associated with investing in human capital, however, come in the form of foregone earnings in the sense that the time spent acquiring new skills is at the expense of time that could have been devoted to paid employment. In addition, firms and workers may incur direct costs when investing in training, such as the payment for materials and tuition fees. Using these ideas, Becker (1962) discussed how human capital accumulation is an explanation for the observation of concave age-earnings profiles, since the incentive to invest in new skills is greatest when workers are young and there are a high number of periods over which the future gains may be received.

Following Becker, Ben-Porath (1967) presented a more formal model of the relationship between human capital investment and earnings over the life cycle. Unlike the initial contributions of Becker and Mincer, who present separate discussions for investments made during the schooling and post-schooling phase of the life cycle, Ben-Porath's description incorporates all parts of the life cycle within a single model. In addition, Ben-Porath formally introduces the production technology for the generation of human capital into the analysis and the corresponding effect that the parameters of the production function have on the decision to invest in each period. For each period of the life cycle, individuals choose to invest in producing new units of human capital up to the point where the marginal cost of a unit equals the marginal benefit. Marginal cost is an increasing function of the quantity of human capital produced, whereas marginal benefit is independent of the quantity produced, but declines over time as the number of periods over which the future wage gains from the investment may be received falls. This produces the result that investment is always positive and declining over the life cycle, except at the date of retirement where the marginal benefit of an additional unit of human capital falls to zero. At early stages of the life cycle, where the marginal benefit is particularly high, individuals choose to invest in a sufficiently high quantity of human capital that all of their available time is devoted to investment. This corresponds to the full time schooling phase of the life cycle, where the individual specialises in investment and opts out of the labour market. Following entry into the labour market, the positive and declining optimal investment ratio generates the result that the individual's earnings capacity grows at a declining rate. The actual earnings received by the worker displays a similarly concave profile, but in each period where positive investment occurs, actual earnings are lower since part of the individual's earnings capacity is sacrificed in order to produce new units of human capital. The concave relationship between actual earnings and labour market experience is a key prediction of the Ben-Porath model and is incorporated within many empirical studies examining the determinants of earnings.

Human capital theory has become a powerful tool for helping to explain the wage differentials that exist between workers. It is often argued that differences in human capital accumulation account for a proportion of the observed wage gap between males and females. With female workers anticipating spells out of the labour force for child raising purposes, the incentive to invest in human capital is weakened due to a shorter time horizon over which the benefits of the investment can be received. Over time, the earnings of female workers are then predicted to fall behind those of males. In the UK, there exists a number of studies that attempt to understand why females earn less than males by decomposing the observed wage differential into two components (Greenhalgh 1980; Zabalza and Arrufat 1982, 1985; Miller 1987; Joshi and Newell 1987). The first of these components is referred to as an 'explained' component in that it captures the proportion of the wage differential due to males and females possessing different characteristics, and the proportion due to spells of non participation undertaken by women only. These studies, however, are primarily concerned with the remaining 'unexplained' component of the wage differential. This is interpreted as discrimination in that it reflects differences in the rate of return to characteristics such as schooling and experience between males and females. The contributions that these explained and unexplained components make to the gender wage gap are found to vary considerably among different studies. For example, Miller (1987) finds that two-thirds of the wage gap is attributable to differences in observable characteristics and the effects of non participation, while the remaining one-third reflects discrimination.

As discussed by Wright and Ermisch (1991), however, the standard decomposition technique may lead to the discrimination component being overstated. This is most easily understood by referring to Mincer and Polachek's (1974) important contribution to the literature relating to the earnings profile of intermittent labour market participants. In their theoretical analysis, Mincer and Polachek show that the rate of return to a year of experience depends on the proportion of the current human capital stock that is devoted to investment rather than earning a wage, and the return per unit of investment. Female workers anticipating a career break would be expected to select a lower optimal investment ratio in each year leading up to the interruption. As a result, the rate of return to experience for women may be observed as being less than that of males, even though the return per unit of investment that is undertaken may be identical for the two cases. Under these circumstances, the lower rate of return to experience observed for women does not reflect discrimination, but differences in the optimal amount of investment undertaken in each year. For the decomposition technique described previously, however, any observed difference in the rate of return to experience between males and females is attributed to discrimination. Failure to recognise that part of the difference in the rate of return to experience between men and women is due to differences in the quantity of investment undertaken in each year of labour market experience is likely to overstate the extent of direct discrimination.

In the empirical part of their study, Mincer and Polachek attempt to estimate the direct effect that different career patterns have on the optimal investment decisions of women during the post-schooling phase of the life cycle. The results obtained using US data suggest that single women are associated with higher rates of return to experience than married women with children. The difference in these estimated coefficients is believed to be driven by the impact that the optimal investment ratio exerts on the overall rate of return rather than any differences in the return received per unit of human capital investment across the different groups of women. This offers some evidence, therefore, that individuals anticipating career breaks devote a lower proportion of their time to investment in each year of labour market experience accumulated in the post-schooling phase of the life cycle.

In addition to lowering the optimal investment ratio during periods of paid employment, human capital theory also predicts that women anticipating spells of non participation will have a weaker incentive to invest in the full time schooling phase of the life cycle. The implications that a lower investment ratio has during the schooling phase, however, differs to that during the post-schooling phase of the life cycle. In periods of paid employment, for an additional year of experience accumulated by males and females, a lower investment ratio among females lowers the quantity of new units of human capital produced by females in that year relative to males. As shown by Mincer and Polachek, this may result in the estimated rate of return per year of experience being lower for females. Full time schooling, however, is a discrete choice which individuals are either engaged in or not. A weaker incentive to invest in human capital is likely to reduce the total number of years women choose to remain in schooling, rather than affect the amount of human capital produced per year of schooling. Under these circumstances, the effect of anticipated career breaks is to lower the quantity of schooling that women are observed to have invested in relative to males. In terms of the decomposition technique, this difference in the amount of schooling accumulated by males and females would be captured by the explained component of the wage gap. Evidence from existing UK studies suggests that differences in observable characteristics such as levels of schooling do account for a significant proportion of the gender wage gap.[1] Given its apparent importance in explaining the wage differential between males and females, it would appear useful to explore in more depth the effect that the anticipation of future career breaks has on the quantity of schooling that females choose to invest in.

The first substantial part of the thesis examines the effect that the anticipation of non participation has on the early investment decisions of females. Using a simple life cycle model of human capital accumulation, chapter 2 begins by showing how the expectation of a career break reduces the incentive to invest relative to those planning continuous labour market participation. A consequence of this is that intermittent participants will devote fewer of their early years to full time education and, therefore, enter the labour market at a younger age. With a lower stock of human capital at the point of entry, women who go on to experience spells of non participation in the future would be predicted to receive lower earnings in their first jobs. If there is no discrimination between males and females in the sense that their rates of return to schooling are equal, the observed wage differential at the point of entry may be explained in terms of the differing quantities of schooling that individuals choose to invest in. Chapter 2, therefore, tests a relatively specific aspect of

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[1] Miller (1987) finds that differences in personal characteristics account for 23% of the male-female wage differential.

human capital theory where the expectation of non participation weakens the incentive to invest in full time education.

Examining the relationship between future non participation and starting salaries has some advantages when testing the theory of human capital as it relates to interrupted careers. Most existing studies consider the effect that past spells of non participation have on current labour market earnings (Mincer and Polachek 1974; Mincer and Ofek 1982; Swaffield 2000). Within this empirical framework, the negative estimated coefficient associated with years of non participation is often interpreted as capturing the extent to which the stock of human capital depreciates during time spent out of the labour force. As the UK studies relating to discrimination suggest, this depreciation effect associated with non participation accounts for a relatively large proportion of the gender wage gap.[2] For the statistical analysis presented in chapter 2, however, the interpretation of the effect of non participation is different. Since the spells of non participation have yet to be undertaken at the time starting salaries are observed, the coefficient associated with years of non participation does not capture any depreciation effect. Any observed negative relationship between future non participation and starting salary will reflect the effect that the expectation of intermittent participation has on the quantity of schooling transferred into the labour market. This empirical methodology, therefore, enables an understanding to be gained concerning the effect that planned non participation has on the earnings of women relative to men at the point of labour market entry. The advantage of looking at the gender wage gap in terms of starting salaries, rather than earnings later in the life cycle, is that such a gap is observed before any effects associated with discrimination and depreciation occur. The wage differential that exists at the point of entry may then be primarily attributed to differences in human capital accumulation between males and females.

Some studies have been undertaken with US data using the methodology of relating future participation plans to earnings at an earlier date in the life cycle (Gronau 1988; Blau and Ferber 1991; Sandell and Shapiro 1980). In general, these studies only consider human capital investment decisions made in the post-schooling phase of the life cycle, which offers slightly different predictions concerning the effect that non participation has on starting salaries. In particular, for males and females entering the labour market at the same time, the starting salaries of women is predicted to be higher as a result of them devoting less of their potential earnings capacity at the point of entry to investing in additional human capital. From an

[2] Zabalza and Arrufat (1982, 1985) find that 70% of the differential is due to the depreciation effect of non participation. Lower estimates of 25-30% and 43% are identified by Wright and Ermisch (1991) and Miller (1987) respectively.

empirical point of view, these studies are the most directly related to the statistical analysis undertaken using UK data in chapter 2, and are discussed in more detail within that chapter. The key difference is that the analysis in chapter 2 is based on a human capital model considering investments made over the whole life cycle and not just those made on-the-job. This version of human capital theory predicts that the anticipation of non participation lowers starting salaries as consequence of devoting less years to full time education. Using data from the National Child Development Study (NCDS), some evidence is found to support these predictions. Women experiencing any interruption to their careers by the age of 33 are found to enter the labour market significantly earlier and with 10% lower starting salaries than similarly able males with no such interruptions. No evidence is found, however, that a significant wage gap exists at the point of entry between males and females with continuous participation. Further investigation of the effects of career breaks among females reveals that each year spent out of the labour force induces earlier entry and lowers initial earnings by 1%, with both effects being statistically significant. The negative effect of non participation on the date of labour market entry remains significant when the model is re-estimated by two stage least squares (2SLS) in order to allow for the possible endogeneity of non participation. For the effect on starting salaries, however, the magnitude remains at 1% but is no longer statistically significant.

The earnings equation estimated in chapter 2 is based on the hypothesis that future career plans systematically affect starting salaries through the quantity of schooling that individuals choose to invest in. The reduced form nature of this equation, however, means that the relationship between the quantity of schooling and earnings is not directly tested. This issue is addressed in chapter 3 where a structural earnings equation is estimated in order to calculate the effect that each year of schooling exerts on the earnings at age 33 of members of the NCDS cohort. In most existing studies attempting to estimate the rate of return to schooling, a single estimate is derived reflecting the average rate of return among all of the individuals included in the sample. Some individuals within the sample will be associated with a rate of return to schooling above the average, while others will earn a return below the average. The rate of return to schooling may vary across individuals in this manner if the quality of education received differs across geographic areas. This hypothesis is incorporated into the analysis in chapter 3 by estimating a wage equation that enables the rate of return to schooling for each of the local education authorities (LEAs) in England and Wales to be identified. It would be expected that LEAs observed as having the highest return per year of schooling offer the highest quality education. This link is directly tested in the second stage of the statistical analysis by regressing the estimated LEA-specific rates of return obtained from the earnings equation on a set of variables capturing the average quality of schools contained within each of the LEAs. The measures of quality used are the pupil-teacher ratio, average teacher salary, and expenditure per pupil. In addition to these quality measures, a range of control variables are included reflecting various environmental characteristics of the LEAs, such as the level of deprivation and population density.

The first stage of the statistical analysis presented in chapter 3, which involves obtaining LEA-specific estimates of the returns to schooling, shares much in common with the existing literature relating to the effect that schooling has on earnings. In recent years, some researchers have argued that despite the existence of various sources of bias, ordinary least squares (OLS) estimates of the return to schooling may, afterall, be reliable (Card 1999; Dearden 1999a). This is because there is a tendency for the effects of the differing sources of bias to offset each other. In particular, the omission of ability controls from the earnings equation is expected to lead to the average return to schooling being overstated, while the potential endogeneity and measurement error associated with years of schooling may generate a downward bias. Recent research suggests that estimates of the return to schooling are indeed biased in this way. In the UK, using data from the NCDS, Dearden (1999b) finds that the OLS estimate of the return to education is reduced from approximately 7% to 5% following the inclusion of additional control variables relating to ability. A common technique used in US studies to eliminate the effects of ability bias is to examine differences in education and earnings for a sample of twins, who are assumed to possess similar levels of ability (Taubmann 1976). Recent evidence in the UK provided by Bonjour *et al* (2000) shows that the estimated return to education is around 4% when examining pairs of twins compared to almost 8% in a conventional wage equation. The most common technique used in the literature to correct for the downward bias associated with measurement error or endogeneity is to use 2SLS. This requires the use of suitable instruments to explain exogenous variation in years of schooling. One possible choice of instrument relates to legislation concerning the amount of time individuals are required to remain at school (Angrist and Krueger 1991). Using this approach for UK data, Harmon and Walker (1995) find that the return to education is 15%, which is more than double their OLS estimate.

In the light of Dearden's (1999a, 1999b) research using the NCDS, the earnings equation in chapter 3 enabling the rate of return to schooling to be identified for each LEA in England and Wales is estimated by OLS. In the second stage of the analysis, these LEA-specific rates of return are regressed on a set of variables measuring the average level of quality of the schools contained within each LEA. This approach is essentially a simplified version of Card and Krueger's (1992) two stage methodology, where the quality of education is believed to influence subsequent labour market earnings through the rate of return to schooling. Existing studies that have been undertaken in the UK to analyse the wage effects associated with school quality have employed an alternative methodology. Using the NCDS, Dearden *et al* (1998), and Harmon and Walker (2000) estimate a conventional earnings equation that includes the standard measures of school quality as additional variables. In this single regression approach, quality is hypothesised as influencing earnings by shifting the entire relationship between years of schooling and earnings upwards in a parallel manner. The results obtained from these studies, however, find no evidence for the existence of any significant quality effects. The advantage of the two stage approach described in chapter 3 is that it initially determines whether the rate of return to schooling varies across different LEAs before attempting to ascertain whether the variation in the LEA-specific returns may be attributable to the variation in the quality of education.

The statistical analysis presented in chapter 3 shows that for the NCDS cohort, who received their secondary education in the 1970s, there is considerable variation in the LEA-specific returns to schooling. Measured at the age of 33, the rate of return ranges from 6.3% to 18.3%, with a mean of 10%. This average value is slightly greater than the estimates of the return to schooling obtained by Dearden (1999b) who also uses the NCDS. It is important to note, however, that the measure of schooling used in chapter 3 differs from that used in existing empirical studies. As in chapter 2, the point at which the individual enters the labour market for the first time is used to capture the quantity of schooling invested in. In order to check whether the use of entry dates as a measure of schooling is valid, the equation generating the LEA-specific returns to schooling is also estimated using a more conventional measure of schooling, but is found to have little influence on the results. For the second stage of the analysis, the standard measures of quality are found to exert no significant effects on the LEA-specific returns to education. Despite using an alternative methodology, therefore, the evidence given in chapter 3 seems consistent with previous UK studies. In these studies, quality exerts no direct effect on earnings, whereas the analysis in chapter 3 finds that higher school quality has no significant effect on subsequent earnings as a result of raising the estimated rate of return to schooling. Overall, previous UK research and the material covered in chapters 2 and 3 suggest that the quality of education individuals receive is not as important a factor in determining earnings as the quantity of education.

Chapters 2 and 3 are essentially concerned with human capital investments undertaken in the years prior to entry into the labour market. Once the schooling phase of the life cycle is completed, human capital theory predicts that individuals will continue to invest in additional productivity enhancing skills whilst employed within a job. As individuals move closer to the date of retirement, however, the incentive to invest in such on-the-job training is reduced.

This pattern of investment leads to the prediction that during the post-schooling phase of the life cycle, earnings continue to grow but at a diminishing rate (Ben-Porath, 1967). Many studies examining the determinants of earnings test this prediction by including years of labour market experience within the earnings equation. As shown by Mincer and Polachek (1974) the coefficient associated with experience in such an equation may be interpreted as reflecting the optimal investment ratio of workers. The empirical literature generally finds that the coefficients associated with years of experience and its square in an earnings function are positive and negative respectively, suggesting that earnings-experience profiles are indeed concave. The results obtained in chapter 3 also support this finding where, in order to derive LEA-specific estimates of the return to schooling, years of labour market experience is included within the earnings equation.

It is often argued, following the work of Becker (1962), that the coefficient associated with experience in an earnings equation actually reflects the rate of return to investments in general human capital. This type of human capital raises a worker's productivity in all firms and so represents a stock of skills that workers may transfer from one job to another. The years spent engaged in full time schooling is often viewed as raising an individual's stock of general human capital. In addition to general human capital, Becker also identified an alternative type of on-the-job training. Specific human capital relates to the stock of skills a worker accumulates within a particular job and which only increases productivity while the match with the current employer is maintained. If a worker leaves their current employer, the skills accumulated that were specific to that job are lost, leaving only the worker's stock of general human capital to be taken into any subsequent firm. This theoretical distinction between different types of human capital has been transferred into the empirical literature by including years of tenure with the current employer as an additional explanatory variable in the earnings equation alongside experience. In such an equation, the coefficients associated with tenure and experience are interpreted as capturing the returns to specific and general human capital investments respectively. The earnings-tenure profile is also predicted to be concave since the incentive for firms and workers to acquire specific human capital is greatest early on in the employment match.[3] Evidence from existing studies generally supports this pattern of specific human capital accumulation.

The observation of earnings profiles that are concave with respect to experience and tenure is often seen as providing strong evidence in support of the theory of human capital

[3] Bartel and Borjas (1978), however, show that human capital accumulation within a job may initially increase before declining as workers revise their expectation of the job duration.

accumulation. There are, however, alternative explanations for the existence of such concave profiles that may arise if workers undertake a series of job changes during their working lives. Theories of job mobility rely on the assumption that the labour market is characterised by some degree of heterogeneity and imperfect information. Most models assume that there exists a range of firms that differ in terms of the tasks that workers are required to perform. Workers enter the labour market with a stock of skills that may be applied to each of the available jobs. The wage that a worker receives in a particular job depends on their productivity, which is related to how useful their stock of skills are in performing the necessary tasks. In some models (Mortensen 1988), imperfect information exists in that a worker's actual productivity in a job is not known at the beginning of the employment match. As the worker accumulates job tenure, additional information relating to their actual productivity is revealed to the firm. In the light of this new information, the firm adjusts the wage it pays the worker, in either a positive or negative direction. If the greatest adjustments occur early in the job match, such a process of information accumulation is capable of generating a concave earnings-tenure profile independently of any human capital investment. A worker who quits one job and engages in a new employment match starts the information accumulation process from the beginning. It is then possible that their rate of growth of earnings in the early years of the new job exceeds the rate of growth of earnings that they would have received by continuing in the previous job.

Models of job mobility involving imperfect information, therefore, offer predictions concerning the effect that a job change has on the slope of the earnings profile. It is also possible, however, that the instantaneous effect of switching job may see a worker's earnings profile shift up or down. This will occur if the starting salary in the new job differs from the final wage received in the previous job. The models incorporating information accumulation offer some predictions relating to the vertical shift of the profile following a job change. In Mortensen's approach, workers may be willing to accept a pay cut at the point of job change in order to move on to a steeper wage profile. Whether their earnings profile actually shifts up or down will then depend on the initial wage offered to them from an alternative firm. The offers that workers receive relating to starting salaries may be dependent on the intensity at which they search for new jobs. One of the simplest search models, described by Burdett (1978), is often referred to in the mobility literature to illustrate how switching jobs shifts the earnings profile. As in the matching models, actual productivity on any job remains constant, but there is perfect information surrounding the level of productivity. Workers are then faced with a distribution of wage offers derived from their varying productivity in the available jobs. The job that an individual takes at the point of entry may be interpreted as a random draw from this distribution. Over time, the worker searches for an alternative job in which their stock of skills may be used more productively. Each time such a job is found, their earnings profile will shift upwards, but remain horizontal. As the worker moves further along the wage offer distribution, the potential wage increments associated with switching jobs declines and the time interval between receiving superior wage offers increases. The earnings-experience profile is then constructed from a series of steps which, when smoothed out, appears concave in nature.

The theoretical models of job mobility all predict that in the long run, voluntary job changes will increase lifetime earnings. Workers will only choose to switch jobs if the present value of future earnings in an alternative job exceeds that of the current job, after any mobility costs have been incurred. This long run mobility wage gain is obtained as a result of shifts in the earnings profile and changes in its slope. Different theoretical models offer different predictions relating to the direction that each of these two separate components take, although the combined effect always produces a wage gain in the long run. For example, Mortensen's (1988) approach suggests that the earnings profile may shift down and becomes steeper following a job change, whereas in the model considered by Eriksson (1989), the profile shifts up and becomes flatter. In the empirical analysis presented in chapter 4, an attempt is made to gain a detailed understanding of the wage effects associated with job mobility. Using data from the British Household Panel Survey (BHPS), separate wage change equations are estimated for males and females in order to calculate the total wage gain received by workers who switch jobs over the period 1991-1994. In addition, the methodology adopted also enables the total wage gain to be decomposed into the separate effects that mobility has on both the slope and vertical positioning of the earnings profile.

Existing empirical studies of job mobility have concentrated on estimating the aggregate of the two wage effects identified by Mortensen and others, which is referred to as the long run mobility wage gain. There are two main approaches within the literature for estimating the magnitude of this long run gain associated with mobility. The first methodology calculates the wage gain by estimating separate wage equations for those who switch jobs and those who do not using Heckman's (1979) procedure to correct for the selection effects associated with the groups of movers and stayers (Borjas and Rosen 1980; Kidd 1991; Simpson 1990). Using this approach with Swedish data, Holmlund (1984) calculates the annual average wage gain associated with mobility to be around 2%. In the second approach, a single wage change equation is estimated where an individual's mobility status is captured by a dummy variable (Abbott and Beach, 1994). By estimating a wage change equation incorporating a dummy variable indicating those who switch jobs over the relevant period, the observed difference in wage growth between movers and stayers could be interpreted as an estimate of the long run mobility wage gain. This estimate may be biased, however, if the wage change of stayers does not accurately reflect the change in earnings that the group of movers would have received had they not switched jobs. Following Mincer (1986), Abbott and Beach argue that a more reliable estimate of the mobility wage gain may be calculated by comparing the growth in earnings over the current period of those who switch jobs with those who remain in their jobs in the current period, but who switch jobs in the subsequent period. These "future movers" may be relatively similar in terms of their observable and unobservable characteristics to the group of current period movers. Under these circumstances, the observed wage growth of future movers may be used to proxy the wage growth that the current period movers would have received had they not switched jobs. Using this approach, Abbott and Beach calculate the total mobility wage gain over a one year period for Canadian women to be approximately 8%.

The existing evidence from other countries, therefore, provides estimates of the total wage gain associated with job mobility. These estimates are referred to as long run wage gains since they incorporate any wage effects relating to a vertical shift in the earnings profile and to a change in its slope. In the first part of the statistical analysis presented in chapter 4, an attempt is made to derive an estimate of the long run mobility wage gain over a three year period using data from the BHPS. In order to do this, an empirical methodology is used that is similar to that of Abbott and Beach. A wage change equation is estimated for the period 1991-1994 with the inclusion of a dummy variable capturing those who switch jobs at some point during the current period. In order to proxy the change in earnings that these current movers would have received had they not switched jobs, an additional dummy variable is included for future movers, who are defined as workers remaining in their jobs in the 1991-1994 period, but who switch jobs in the following 1994-1997 period. By comparing the change in earnings of current movers with future movers over the 1991-1994 period, the long run mobility wage gain is estimated to be 11% for males and 9% for females.

Following the estimation of the long run mobility wage gain, the statistical analysis in chapter 4 then attempts to determine the effect that a job change has on the earnings profile in terms of its gradient and vertical positioning. This is achieved by extending the dummy variable methodology used by Abbott and Beach. In addition to examining individuals' mobility status over the current and future periods, information is also used relating to job changes occurring in the previous three year period, 1988-1991. The observed wage growth in the current period of "past movers" is interpreted as reflecting the slope of the earnings profile in the early years of a new job. This may then be compared to the wage growth in the current period of the group of future movers, who are on the verge of switching jobs. Since neither of these two groups of workers switch jobs in the period over which the wage change equation is estimated, neither experience any shifts in their earnings profiles. Any difference in their observed growth in earnings, therefore, reflects differences in the slopes of their corresponding earnings profile. If past movers and future movers possess similar characteristics, comparing their earnings growth may offer an insight into the effect that mobility has on the slope of the earnings profile before and after the job change. Once the effect of mobility on the slope of the profile has been calculated, the remaining part of the total wage gain may be attributed to the vertical shift that occurs at the point of job change. The results obtained in chapter 4 using this decomposition technique suggest that for men, approximately three-quarters of the total mobility wage gain over the period 1991-1994 may be attributed to the earnings profile become steeper, and one-quarter due to an upward shift in the profile. For women, however, each of the individual wage effects are found to make approximately equal contributions to the long run mobility wage gain.

Chapters 2 to 4, therefore, form a series of statistical analyses of some of the main factors that determine the earnings of UK employees over their working lives. Following much of the existing literature, the first two substantial chapters concentrate on the theory of human capital as the main driving force behind lifetime earnings. As has been widely noted, differences in human capital accumulation account for a significant proportion of the observed wage differential that exists in later life between males and females. Chapter 2 attempts to determine whether a significant gender wage gap exists at the point of labour market entry. Females may be expected to receive lower starting salaries than males if the anticipation of future career breaks weakens the incentive to invest in full time education. The model developed in chapter 2, however, does not directly test the relationship between the quantity of education received and subsequent earnings. This issue is explored further in chapter 3, where an estimate is obtained for the effect that each additional year of schooling has on the earnings of members of the NCDS cohort at age 33. The methodology used enables separate estimates of the return to schooling to be obtained for each of the local education authorities in England and Wales. These estimated returns are then regressed on variables capturing the quality of education in the LEAs in order to determine whether the quality of education is as important a factor in determining earnings as the quantity of education. When looking at earnings at age 33, the results in chapter 3 also show that earnings increase with labour market experience at a diminishing rate. This result is consistent with the theory of human capital accumulation, but part of the observed positive returns associated with experience may be attributable to the long run wage gains that workers receive when they voluntarily switch jobs. Chapter 4 uses an alternative data set, the BHPS, to estimate the extent to which earnings increase over a three year period following a job change. The panel nature of the data is exploited in order to not only estimate the total wage gain, but also to identify the separate influences on the positioning and slope of the earnings profile. The existence of significant wage gains associated with mobility suggests that identifying jobs in which their skills are best suited is a key factor in determining a worker's lifetime earnings.

Chapter 2 Interrupted Work Careers and the Starting Salaries of Female Workers in Britain

2.1 Introduction

A popular area of research in labour economics concerns the observed wage differential between male and female workers. In the UK, several studies have been undertaken that attempt to identify the factors responsible for creating this gender wage gap. The emphasis of these studies, however, is placed on estimating the extent to which discrimination exists within the labour market and the impact that legislation in the 1970s has had on reducing such discrimination. One of the interesting features of these studies is that a large proportion of the gender wage (66% in the case of Miller 1987) is explainable in terms of differences in observable personal characteristics and the effect of time spent out of the labour force. Each year that women spend out of the labour force lowers subsequent earnings relative to males in three main ways. Firstly, it is normally assumed that no further human capital investments are undertaken during the years of non participation. Secondly, the existing stock of skills depreciates during the career break, placing women at a disadvantage when they re-enter the labour market. In addition, female workers anticipating spells of non participation may choose to invest in less human capital than males in the years leading up to the interruption. This third effect creates a wage differential even before women experience interruptions since they are observed with a lower stock of human capital. There are a number of studies that generally estimate the first two of these effects by relating a worker's current earnings to past spells of participation and non participation (Mincer and Polachek 1974; Corcoran and Duncan 1979; Swaffield 2000). Most of these studies find that past periods of non participation negatively affect current earnings, with Mincer and Ofek (1982) calculating the total cost of a year of non participation to be approximately 1.5%. This is interpreted as a total cost since it indicates the wage penalty that arises from sacrificing a year of human capital accumulation plus the depreciation of the existing capital stock.

An alternative approach for analysing the effect of interrupted careers is to relate earnings at a particular point in time to spells of non participation occurring in the future (Gronau 1988; Blau and Ferber 1991). The advantage of this methodology is that it enables the effect that future non participation has on the incentive to invest in human capital to be isolated. This is because at the time at which earnings are observed, the spell of non participation has yet to occur. Any negative impact that a year of future non participation is found to exert on current earnings is then free of any depreciation effect associated with time out of the labour force. Since the year of non participation has not yet been realised, the negative coefficient also does not capture the year's worth of human capital accumulation that is sacrificed by being out of the labour force. Instead, a negative relationship between current earnings and future non participation reflects the extent to which the anticipation of career breaks weakens the incentive to invest in human capital in the years prior to the break occurring. Women who anticipate taking time out of the labour force will accumulate less human capital earlier in their lives, generating a gender wage gap in the years before their career plans are realised.

This chapter analyses the effect that future spells of non participation have on the starting salaries of women relative to men of similar ability. By developing a model that considers human capital investments undertaken over the complete life cycle, it is possible to show that women planning interrupted careers will devote a lower proportion of their time to human capital accumulation in each period prior to the break commencing. An important implication of this is that women will spend fewer of their early years engaged in full time education and, therefore, enter the labour market at an earlier date than those planning continuous participation. With intermittent participants transporting a lower stock of human capital into the labour market, their earnings at the point of entry are predicted to be lower. Using data from the National Child Development Study (NCDS), an attempt is made to find evidence for the idea that future periods of non participation induce women to enter the labour market at an earlier date and with a correspondingly lower starting salary. One of the advantages of estimating an earnings equation of this form is that it enables the gender wage gap to be detected at the earliest observable time. Existing UK studies tend to examine the wage gap at a point later in the life cycle and then consider the proportions of the differential that are due to differences in stocks of human capital, the depreciation effect of non participation, and discrimination. Since the methodology adopted within this chapter examines initial earnings, which are observed before any career interruptions take place, the observed gender wage gap in starting salaries is attributed purely to differences in the quantity of human capital taken into the labour market. The analysis may therefore be seen as focusing on the effect that future career breaks have on the early investment decisions of women relative to those planning continuous participation in the labour market.

The remaining sections of the chapter are structured in the following way. Section 2 outlines the human capital model that is used to obtain the predictions concerning the effects that career interruptions have on the investment decisions and starting salaries of individuals. Section 3 then presents a review of some of the existing literature that has analysed the effect that future participation plans have on the earnings of male and female workers. In the fourth section, the sample of individuals extracted from the National Child Development Study (NCDS) is described and some summary statistics are presented as a way of offering some preliminary evidence for the theoretical predictions concerning the effects that career breaks have on labour market entry dates and starting salaries. Section 5 then describes the statistical model used in this study and presents the results obtained from estimating the entry date and starting salary equations. The results obtained from the NCDS suggest that women experiencing any kind of interruption by the age of 33 enter the labour market at a significantly earlier date and with 10% lower starting salaries than comparable men. Further estimations for the sample of women find that each additional year spent out of the labour force lowers initial pay by 1%. The magnitude of this effect remains at 1% when the starting salary equation is re-estimated by two stage least squares (2SLS) treating non participation as endogenous, but the statistical significance is reduced. The final section of the chapter then summarises the main findings of the statistical analysis and discusses some of its possible limitations.

2.2 The life cycle human capital approach and interrupted work careers

In this section, a theoretical framework is outlined that may be used to compare the human capital investment decisions of those individuals who plan continuous participation throughout their working lives and those anticipating a spell of non participation. In the model presented below, individuals are assumed to be able to perfectly plan their lifetime labour market participation and that there is no discrepancy in any time period between planned participation and realised participation. For the case of workers planning continuous participation it is shown that the optimal proportion of time allocated to human capital investment declines over time from a value equal to one during periods of full time education to a value equal to zero at the date of retirement. It is this positive and declining optimal investment ratio that generates an earnings profile over the course of the working life that is concave in nature. By introducing a career break into the model, it may be shown that the optimal investment ratio will be lower in each period prior to the break occurring for those planning intermittent participation compared to those expecting continuous participation. With a lower investment ratio in each period, it is predicted that those planning career breaks will devote less time to full time education, enter the labour market earlier, and be associated with a lower starting salary. The model may also be used to show that the starting salary of individuals planning intermittent participation declines with the length of the break and increases with the age at which the break commences.

2.2.1 The continuous participation case

The benefit to an individual planning continuous participation from investing in an additional unit of human capital at time t is to raise their potential earnings in each subsequent period until the date of retirement, T. If such investments depreciate at a rate equal to δ then the increase in potential earnings in period τ (where $\tau > t$) arising from the investment undertaken at t may be written as:

$$wI(t)e^{-(r+\delta)(\tau-t)}$$

where w is the wage per unit of human capital and r is the discount rate

The full benefit to the individual from the investment at t in terms of the increase in potential earnings over the remaining periods of the life cycle may then be found by integrating the above expression between $\tau = t$ and $\tau = T$:

$$B(t) = \frac{wI(t)}{r+\delta}\left[1 - e^{-(r+\delta)(T-t)}\right] \tag{2.1}$$

The link between the proportion of time allocated to investment, $x(t)$, and the resulting amount of human capital produced is given by the following production function:[1]

$$I(t) = Ax(t)^b K(t) \tag{2.2}$$

where A and b are productivity parameters relating to the individual or the institution in which the investment is undertaken

Using the benefit function, the production function and a cost function that considers the cost of human capital investments only in terms of foregone earnings (see appendix A), it may be shown that the optimal proportion of time allocated to investment in any period for those planning continuous participation, $x^*_{CP}(t)$, is given by:

$$x^*_{CP}(t) = \left\{\frac{Ab}{r+\delta}\left[1 - e^{-(r+\delta)(T-t)}\right]\right\}^{\frac{1}{1-b}} \tag{2.3}$$

[1] This form of production function is common within the human capital literature and produces the result that the investment decision in any period is independent of the current stock of human capital.

Inspection of (2.3) reveals that as t increases, the term $e^{-(r+\delta)(T-t)}$ increases from a value close to zero to a value equal to one when $t = T$. This implies that the optimal investment ratio for those with continuous participation will decline over time reaching zero at the date of retirement. The first and second derivatives of (2.3) imply that $x^*_{CP}(t)$ will initially decline at an increasing rate, but beyond a certain point, the rate of decline will start to decrease.[2] The top curve in figure 2.1 on page 21 depicts the investment profile for individuals with continuous participation in the labour market. Initially the desired value of $x^*_{CP}(t)$ obtained from solving the optimisation problem may exceed the value of one, in which case the actual optimal investment ratio will be set to its maximum value of one, but over time it will decline and eventually reach zero at the retirement date. The time horizon over which $x^*_{CP}(t)$ is constrained to being equal to one relates to periods of full time education and is denoted by S_{CP}. By setting the left-hand-side of (2.3) equal to one and solving for t, it is possible to derive the following equation for the number of periods devoted to full time education among continuous participants:[3]

$$S_{CP} = T + \frac{\ln(1 - 1/B_1)}{B_2} \qquad \text{where } B_1 = Ab/(r+\delta) \text{ and } B_2 = (r+\delta) \tag{2.4}$$

2.2.2 The intermittent participation case

Consider now the case of individuals who plan to experience an interruption at some point within their working lives. Suppose the interruption occurs in such a way that there is no participation in the labour market between periods g and c (where $c > g$). The benefit to an individual from an investment undertaken at a time before the interruption occurs (i.e. $t < g$) is given by:

$$B(t) = \frac{wI(t)}{r+\delta}\left[1 - e^{-(r+\delta)(g-t)}\right] + \frac{wI(t)}{r+\delta}\left[e^{-(r+\delta)(c-t)} - e^{-(r+\delta)(T-t)}\right] \tag{2.5}$$

In the equation above, the first term on the right-hand-side represents the part of the total benefit of the investment made at t arising from the addition to potential earnings over the period between the time of the investment occurring (t) and the time at which the gap in participation begins (g). The second term on the right-hand-side is the contribution made to the total benefit arising from the effect that the initial investment has on potential earnings from the time that the individual returns to the labour market (c) to the date of retirement (T).

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[2] See appendix A for the derivatives of (2.3).

[3] The derivation of (2.4) is shown in appendix A.

Using the same approach as for the case of individuals with continuous participation, the optimal investment ratio for individuals with interrupted participation, $x^*_{IP}(t)$, may be expressed as:

$$x^*_{IP}(t) = \left\{ \frac{Ab}{r+\delta} \left[1 + e^{-(r+\delta)(c-t)} - e^{-(r+\delta)(g-t)} - e^{-(r+\delta)(T-t)} \right] \right\}^{\frac{1}{1-b}} \qquad (2.6)$$

Equation (2.6), therefore, defines the optimal proportion of time allocated to the acquisition of human capital for an individual with an anticipated break in their lifetime labour market participation. This equation, however, is only applicable for investment decisions made in the periods leading up to the start of the interruption i.e. when $t < g$. During the time of the interruption it is assumed that no investment in human capital occurs and that the individual's earnings are zero. On returning to the labour market, the individual with intermittent participation will have the same sequence of values for $x^*(t)$ for the remaining time periods $(c < t < T)$ as individuals with complete participation, assuming that all parameter values in (2.3) and (2.6) are identical for the two cases. This is because past investments in human capital do not influence the current investment decision which may be seen by noting that the optimal investment ratio in (2.3) and (2.6) is independent of the current stock of human capital $K(t)$. The value of $x^*(t)$ is essentially determined by the number of periods of participation remaining so once the interruption is complete, the incentive to invest for those who have returned to the labour market following a break becomes identical to those with complete participation. This means that the two investment profiles coincide for all $t > c$ until the date of retirement.[4]

The first and second derivatives of (2.6) imply that the shape of the investment profile for individuals with interrupted careers will be similar to that associated with workers with continuous participation with $x^*_{IP}(t)$ initially declining at an increasing rate over a certain range and then falling at a decreasing rate. Analysing equations (2.3) and (2.6) and their associated derivatives enables figure 2.1 to be constructed which illustrates the investment profiles for individuals with continuous participation and interrupted participation.

[4] This is a somewhat extreme consideration of the human capital model. Following re-entry into the labour market there are likely to be strong reasons why the investment profiles for continuous and intermittent participants are not identical. This is beyond the scope of this study which only examines the effect of non participation on the very early labour market experiences of women.

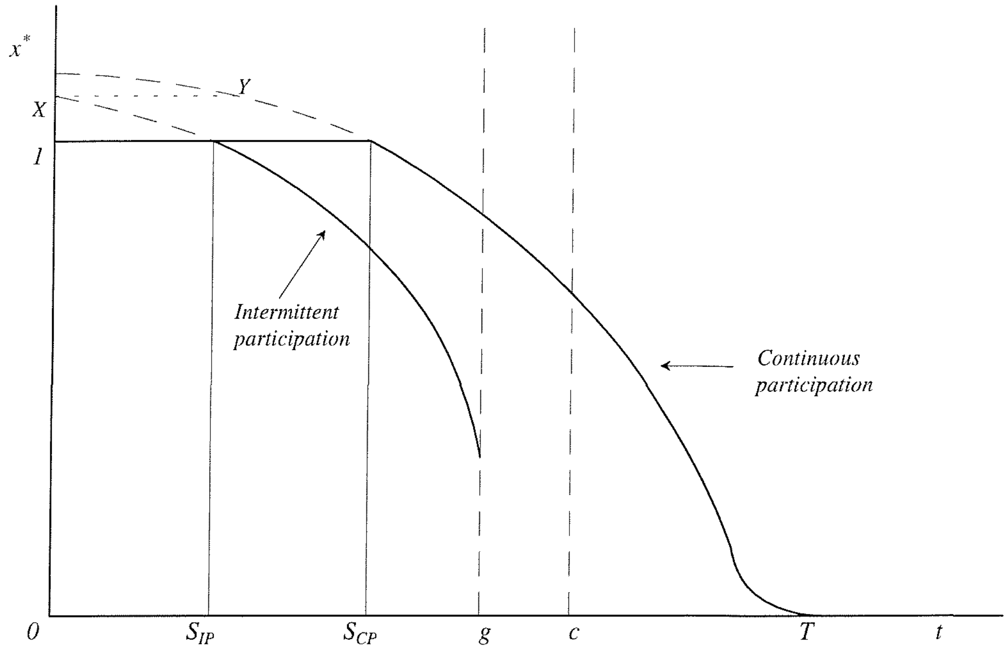

Figure 2.1 The investment profiles of intermittent and continuous participants

The diagram above shows that the optimal investment ratio for intermittent workers will be lower than that of workers with complete participation in every period over the range prior to the start of the break. This result may also be seen by referring to equations (2.3) and (2.6). Denoting $B_1 = Ab/(r+\delta)$, $B_2 = (r+\delta)$, and defining the length of the break as $L = (c-g)$, it may be shown that the difference between the optimal investment ratio for continuous participants and intermittent participants can be written as:

$$x_{CP}^*(t)^{(1-b)} - x_{IP}^*(t)^{(1-b)} = B_1 e^{-B_2(g-t)}\left[1-e^{-B_2 L}\right] \tag{2.7}$$

In (2.7) it can be seen that when no break occurs $(L=0)$, the right-hand-side is equal to zero implying that the optimal investment ratio in any period is identical for the two cases. When a break is planned $(L>0)$, however, the right-hand-side of (2.7) is positive meaning that individuals with continuous participation will be associated with a higher investment ratio in each period than those with intermittent participation. As the length of the break increases, the term in square brackets moves closer to one, increasing the value of the right-hand-side and therefore increasing the differential between the investment ratios of continuous and intermittent workers. It may also be seen in (2.7) that as the start date for the break moves to an earlier date in the life cycle (g falls), the right-hand-side increases which implies that the difference between the investment ratios for the two types of worker widens. The most important predictions of the model outlined in this section, therefore, are that the existence of a career break lowers the incentive to invest for intermittent workers relative to continuous participants and that this differential widens as the length of the break increases and as the break commences earlier in the life cycle.

The other notable feature of figure 2.1 is that as a result of intermittent participants investing in less human capital in each period, the date at which they leave full time education and enter the labour market occurs earlier than for continuous participants. In the diagram, it may be seen that the number of periods over which the optimal investment ratio is constrained to being equal to one is S_{IP} for intermittent workers and S_{CP} for the case of continuous participants. In section 2.1, an expression for S_{CP} was derived by finding the value of t when the optimal investment ratio equalled one. A similar equation may then be derived for S_{IP} by setting the left-hand-side of (2.6) equal to one and solving for t. The date at which the intermittent participant is just on the verge of leaving full time education and entering the labour market is then given by equation (2.8).

$$S_{IP} = T + \frac{\ln(1-1/B_1)}{B_2} - \frac{\ln\left[1+e^{B_2(T-g)} - e^{B_2(T-g-L)}\right]}{B_2} \tag{2.8}$$

The difference in the amount of time devoted to full time education between the two groups may then be found by subtracting (2.8) from (2.7), leading to (2.9) below.

$$S_{CP} - S_{IP} = \frac{1}{B_2}\ln\left[1+e^{B_2(T-g)} - e^{B_2(T-g-L)}\right] \tag{2.9}$$

Inspection of (2.9) reveals that if no break occurs, there will be no difference between S_{CP} and S_{IP} since g will equal T, L will equal zero, and the value of the terms in square brackets will simply be equal to one. When a break does exist, however, g takes a value less than T, L will become positive, and the value of the terms in square brackets will exceed one, creating a positive differential between S_{CP} and S_{IP}. It may also be seen that this differential will widen as the length of the break (L) increases, or as the start date for the break (g) decreases, assuming that all else remains equal between the two groups of individuals.[5]

[5] The effects that changes in the length of the break and its timing have on the schooling differential are verified in appendix A by differentiating (2.9) with respect to L and g.

2.2.3 The role of ability in determining the investment ratio

Sections 2.1 and 2.2 discussed the effect that the introduction of a planned career interruption has on the investment decision of intermittent workers compared to the case of those with continuous participation. It was seen how the existence of a break lowers the investment ratio of intermittent participants relative to continuous participants. Increasing the length of the break or moving the break to a point earlier in the life cycle was also shown to raise the investment differential between the two cases, assuming all the other parameters are the same for both types of workers. In equations (2.3) and (2.6) it may be seen that these other factors influencing the investment ratio are the date of retirement (T), the rate of depreciation (δ), the discount rate (r) and the productivity parameters (A and b), which may be related to ability. In the empirical analysis that follows, a distinction is made between individuals with different levels of ability so it is useful at this point to analyse the effect that ability has on the investment decision. Equations (2.3) and (2.6) reveal that higher values for the parameters A and b will increase the value of the optimal investment ratio in any given period. It may also be seen by referring to the first derivatives given in appendix A that the slope of the investment profile will be steeper the higher the values of A and b are. With more able individuals devoting more time to human capital investment in each period, it follows that such individuals will also devote a larger proportion of their life to full time schooling and thus enter the labour market later. This may be verified in equations (2.4) and (2.8) where more able individuals will be associated with a greater value for the parameter B_1 which has the effect of increasing the number of periods that the individual devotes to full time education. In the empirical analysis undertaken in this study, it is important to control for the effect that ability has on entry dates and starting salaries in order to be able to identify the separate effect that career interruptions have on these two variables.

2.2.4 The effect of human capital investments on earnings

Within the labour market, investments in human capital are rewarded by increasing an individual's potential earnings. Devoting time to investment increases the stock of human capital held by an individual which raises potential earnings in accordance with the market wage per unit of human capital, w. Actual earnings, however, will be less than potential earnings in any period where positive investment occurs since the cost of investment is defined as being the part of potential earnings sacrificed by the individual when they choose to spend a proportion of their time investing rather than earning in the labour market. It may be shown that actual earnings in any period t of the post full time education phase of the life cycle is given by the following expression:[6]

$$\log y(t) = \log(wK_0) + s(A-\delta) + \log\left[1 - x^*(t)\right] + \int_{\tau=s}^{t} \left[Ax^*(\tau)^b - \delta\right] d\tau \qquad (2.10)$$

In this equation, the third term on the right-hand-side represents the negative effect that the current investment rate has on earnings, while the fourth term reflects the positive impact that past investments made on-the-job have on current earnings. The first observable value for earnings occurs just beyond the point when the individual leaves full time education and enters the labour market for the first time. The starting salary may therefore be written as:

$$\log y_{FST} = \log(wK_0) + s(A-\delta) \qquad (2.11)$$

Equation (2.11) is most easily derived from (2.10) by considering an individual who invests in no additional human capital beyond the schooling phase. Their earnings would remain constant and in any period t, would equal the value of their human capital taken into the labour market. Equation (2.11) implies that the starting salary increases with the initial stock of human capital and with the number of years spent in full time education, s. Each year of additional education raises initial earnings in accordance with the rate of return to schooling, $(A-\delta)$. In the previous section, it was shown how the introduction of a planned interruption results in a lower optimal investment ratio for intermittent workers compared to those with continuous participation in each period prior to the break occurring. From figure 2.1, this implies that individuals planning interrupted careers will devote less time to full time education than workers anticipating complete participation, if all else is identical for the two cases. With intermittent workers entering the labour market with lower schooling, it may be seen from (2.11) that these workers will have lower starting salaries than those planning continuous participation, assuming that all other factors are equal.[7] It is this theoretical

[6] See appendix A for the derivation of this equation.

[7] Earlier entrants will be associated with both lower actual and potential earnings. Those with intermittent participation will enter the labour market earlier and with a lower stock of human capital which means that their potential earnings are lower at the point of entry compared to those with continuous participation. Just at the point of entry, the investment ratio for the two types of worker will be the same, marginally below one. With lower potential earnings and the same investment ratio at the point of entry, actual earnings at the time of entry will be lower for intermittent participants than continuous participants. In models that examine on-the-job investments made by men and women entering the labour market at the same time, actual starting salaries are higher for females than males since they have a lower investment ratio in the initial period which brings actual earnings closer to potential earnings.

prediction that forms the basis of the empirical analysis within this study where an attempt is made to find support for the idea that starting salaries for women are systematically related to the length and timing of future career interruptions.

Following entry into the labour market, the earnings profile of those with continuous participation will be concave. Earnings in any period beyond the full time education phase will be positive with the rate of growth of earnings being high at the point of entry and gradually declining over the life cycle. This concavity of the earnings profile arises as a result of the path taken by the optimal investment ratio over time. For individuals with intermittent participation, the earnings profile will be represented by a downward-left shift in the earnings profile associated with continuous participants. The reason for this is that the investment profile for intermittent participants is given by a leftward shift in the investment profile for those with continuous participation. It can be shown that all the points on the investment profile for continuous participants will appear on the profile of intermittent participants at an earlier date. As an example, in figure 2.1, the value of the optimal investment ratio at point *Y* will be the same as the value of the investment ratio at point *X*. This implies that the investment profile of intermittent participants will always be at a more advanced stage than that of continuous participants. Since the earnings profile is determined by the investment profile, it follows that the earnings profile of intermittent participants will also be at a more advanced stage in the sense that it will start at an earlier date and be flatter at any point in time where a positive value of earnings is observed for both intermittent and continuous participants.[8]

2.3 Literature review

There are a number of studies that have been undertaken which attempt to analyse the effect that spells of non participation have on earnings over the life cycle. Most of the existing empirical literature testing the theory of human capital as it relates to intermittent participation considers a model that is slightly different to that presented in section 2 of this chapter. The model outlined in the previous section considers human capital investments made throughout the entire life cycle, whereas most of the existing literature refers to a model that only considers investments undertaken on-the-job, or alternatively, after the completion of full time education. When the analysis is restricted to only include on-the-job investment, it is predicted that those anticipating periods of non participation will be associated with a higher starting salary and a flatter earnings profile than for those expecting continuous labour

[8] This is discussed more formally in appendix A.

market participation. This is because for individuals entering the labour market at the same time, those planning intermittent participation will have a lower incentive to invest in human capital in each subsequent period than individuals planning continuous participation. Both types of worker will have the same potential earnings if they enter at the same time, but with a lower investment ratio in the first period of the post schooling phase, the actual earnings of the intermittent worker will be closer to the common value of potential earnings. In this case, the starting salary of an intermittent worker is predicted to exceed that of a continuous participant. With a lower rate of investment in each period following entry, however, the rate of return for each year of experience will be lower for the intermittent worker, generating an earnings profile that is flatter than that associated with continuous participants. For the model described in section 2 though, the effect of a planned interruption is to weaken the incentive to invest in human capital in each period of the individual's life leading up to the start of the break. As a result, those planning intermittent participation will enter the labour market earlier than those expecting to be continuous participants and earn a lower starting salary as a consequence of entering the labour market with a lower stock of human capital. Following entry into the labour market, intermittent participants and continuous participants will move along concave earnings profiles that are similar in shape, but because intermittent participants entered earlier, at a given point in time when both types of worker are employed, the slope of the earnings profile will be flatter for intermittent workers. The two different versions of the human capital model, therefore, offer slightly different predictions concerning the effect that intermittent participation has on the labour market outcomes of individuals.

Blau and Ferber (1991) attempt to test the hypothesis that female workers will be associated with higher starting salaries and flatter earnings profiles than males. They use data obtained from questionnaires relating to individuals planned levels of labour market participation and anticipated earnings. A series of regressions were estimated for both males and females where expected starting salaries, earnings ten years after graduation, and earnings twenty years after graduation were related to the number of years that each individual plans to work. According to human capital theory, those planning to work more years would be expected to be associated with lower starting salaries, but have higher earnings ten or twenty years after entry into the labour market. In none of the equations estimated, however, were years of participation found to exert any significant influence on earnings leading Blau and Ferber to conclude that planned labour force participation appears to exert little influence on anticipated earnings profiles.

One of the most important issues that needs to be addressed when testing the theory of human capital as it relates to intermittent participation concerns the possible simultaneous determination of earnings and years of participation. The model discussed in section 2 shows that planned periods of non participation influence earnings over the life cycle, but it could be the case that a feedback effect exists in the sense that earnings partly determines individuals' participation decisions. In their study, Blau and Ferber allow for the interdependence between expected earnings twenty years after graduation and planned participation by adopting a two stage least squares (2SLS) approach.[9] Separate equations were estimated for each of the joint dependent variables that included the predicted values of the other potentially endogenous variable as an explanatory variable. Since most of the men in the sample expected to work continuously, Blau and Ferber only estimated these equations for women. In doing this, the results from estimating the earnings equation by 2SLS were similar to the OLS estimates in that the number of years of non participation was found to have no significant effect on earnings. Blau and Ferber also found little evidence to support the feedback hypothesis since, for the other equation in the system, expected salary 20 years after graduation had no significant effect on the number of years an individual plans to work.

Gronau (1988) also explores the issue of interdependence between the planned labour force participation of female employees and their earnings. Using data from the Panel Survey of Income Dynamics, a two equation system is considered involving hourly earnings in 1976 and labour force separations occurring between 1977 and 1979 as the joint dependent variables. Unlike Blau and Ferber who use data on planned participation, Gronau examines the effect that an actual separation between 1977 and 1979 has on the reported earnings of an individual in 1976 and then attempts to detect whether any feedback effect exists where earnings in 1976 influence the decision to leave the labour market in the future. In estimating the earnings equation by OLS, it was found that those who went on to experience a labour force separation in the future were associated with significantly lower earnings in 1976. For the second equation in the system, higher hourly earnings were found to significantly lower the probability of a future labour market separation. In order to allow for the simultaneous nature of the system, Gronau then estimated the equations by 2SLS. In doing this, the existence of an interruption to the working life between 1977 and 1979 was found to have no effect on female earnings in 1976, but significant evidence was found in support of the idea that lower wages encourage separations from the labour market. The 2SLS estimates, therefore, do not appear to provide support for the human capital prediction that those

[9] The authors only present 2SLS estimates for anticipated earnings 20 years after graduation.

planning interrupted careers are associated with lower earnings than those with continuous participation plans.

Like Blau and Ferber, Sandell and Shapiro (1980) also test the hypothesis that women anticipating stronger labour force attachment will be associated with lower starting salaries and steeper earnings profiles. The data used is from the National Longitudinal Survey of Young Women who were aged between 14 and 24 years in 1968. Those women who said in 1968 that they planned to be in the labour force when they were 35 years old were viewed as being those with the strongest commitment to the labour market. A conventional earnings equation was then estimated for the hourly wage in 1973 that included a dummy variable to capture the vertical shift in the earnings profile among those with stronger labour force commitment, and an interaction with years of experience to detect the difference in the slope of the earnings profile for these women. The results obtained suggested that for white women, those planning to be in the labour market at age 35 years were associated with an earnings profile that started from a lower point and was steeper than those who did not plan to work when they are 35 years old.[10]

The empirical evidence reviewed in this section, therefore, provides only limited support for the theory of human capital and interrupted work careers. One of the most important points emerging from these studies is the need to address the issue concerning the possible endogeneity of participation plans when undertaking an empirical investigation into the wage effects associated with career interruptions. The empirical analysis within this study follows a similar approach to that of Gronau where an individual's earnings are regressed on information relating to their actual labour market participation in the future. This study, however, differs from most of the existing empirical literature in two ways. Firstly, it examines the effect that future spells of non participation have on starting salaries rather than earnings at a point later in the life cycle. The version of the human capital model that considers investments made over the whole life cycle and not just the post schooling phase predicts that those planning interrupted work careers will be associated with lower starting salaries as a result of entering the labour market earlier. The second important difference lies in the depth of information relating to future periods of non participation. Instead of just using a dummy variable to capture whether the individual plans or actually experiences an interruption, the data contained within the National Child Development Study allows the amount of time spent out of the labour market and the date at which these interruptions occur

[10] The coefficient for the shift dummy was -0.1058 with a *t*-ratio of -1.85 and the coefficient for the interaction term was 0.0391 with a *t*-ratio equal to 1.65.

to be identified. It was shown in section 2 that an individual's starting salary is predicted to be negatively related to both the amount of time taken out of the labour market and the earlier the interruption occurs within the life cycle.

2.4 Description of the data and summary statistics

The data used in this study is taken from the National Child Development Study (NCDS) which is a longitudinal survey of individuals born in the UK in the first week of March 1958. At this time, there have been five sweeps of the NCDS which were undertaken when the cohort members were aged 7, 11, 16, 23 and 33 years. Most of these five sweeps were referred to in preparing the data set required for the empirical analysis undertaken in this study. The final sample of individuals extracted from the NCDS consists of 1378 men and 1286 women. Although this represents only a small fraction of the total number of individuals within the NCDS cohort (approximately 18,000), the criteria for including individuals in the final sample needs to be relatively strict due to the nature of the theory being tested. Within the questionnaire for the fourth wave of the NCDS, taken in 1981 when the cohort members were 23 years old, there exists a section relating to the individual's first job held since leaving school. From the information given in response to these questions, it was possible to determine the date at which the individual's first job commenced and their gross monthly earnings within that job.[11] Individuals were only included in the final sample if they reported having worked full time in their first ever job and were employees in this job rather than being self-employed.[12] In addition to information regarding start dates and salaries relevant to the first ever job, data was also collected in the questionnaire relating to the socio-economic group associated with the first job, the number of employees working for the firm, and whether the first job was in the private sector or the public sector.

Among the data files that form the fifth sweep of the NCDS, taken when the cohort members were aged 33 years, is a work history file that gives information on the start and end dates for periods of employment and non employment that have taken place in the individual's working life. For the spells of non employment that occur, it is possible to determine whether the individual was unemployed during this time or out of the labour force for child raising purposes. Using the information contained within this history file, it was possible to derive two variables for the women in the NCDS cohort which are important for being able to test

[11] The earnings data is deflated according to the month the first job commenced using the retail price index.

[12] Information concerning the actual number of hours worked in the first job was not available. The cohort member only indicates whether they worked full time, which was defined as working more than 35 hours each week, or part time.

the theory of human capital as it relates to intermittent participation. The first variable that was derived, *NP*, refers to the total number of years that each woman reported being out of the labour force for child raising purposes by the time they were 33 years old. The second variable derived, *GAPSTART*, gives the age of the woman when the first interruption for child raising purposes occurred.

Finally, the sweep of the NCDS taken when the cohort members were aged 11 years was utilised in order to obtain some additional control variables required for analysing the effect that future spells of non participation have on starting salaries. The most important control variable to be included is a measure of the individual's ability. Those who are more able are predicted to devote more time to schooling, enter the labour market later and have higher starting salaries than less able individuals with the same participation plans. The measure of ability used in this study is the total score obtained in verbal and non verbal tests taken at the age of 11 years. The other main set of control variables used relate to the social class of the cohort member's father at the time of the second wave of the NCDS. Father's social class may capture additional differences in underlying ability among the cohort members and also affect the decision concerning the school that the individual is educated at, which could in turn, influence the amount of time spent in full time education.

Table 2.1 presents the means and standard deviations for the starting wage, the date at which the first job commenced and a measure of ability at age 11 for several groups of workers from the sample of 2664 individuals. The sub-samples of individuals considered are designed to reflect the different types of participation plans held among the individuals within the full sample. Men are assumed to represent the continuous participation case and are expected to be associated with similar starting salaries to those women who had taken no time out of the labour force by the age of 33, who are referred to in table 2.1 as *WNB*. The sample of women who did report having experienced an interruption by the time they were 33 (*WB*) are then subdivided into four further groups that differ with respect to the length and timing of their non participation spells. The first group, *WBSE*, consists of women who experienced a 'short/early' break, defined as those with less than four years of non participation and whose first reported spell of non participation occurred before age 26.[13] The remaining three groups consist of women whose breaks may be described as 'short/late' (*WBSL*), 'long/early' (*WBLE*), and 'long/late' (*WBLL*). The purpose of dividing the women reporting an interruption by age 33 into these four groups is to determine whether the length and timing of

[13] The variables *NP* and *GAPSTART* are used in order to determine whether the interruptions are early or late, and short or long.

the break affects the date of labour market entry and initial earnings in the manner predicted by the theory outlined in section 2.

Sample	*N*	*Starting salary (£)*	*Entry date (months)*	*Ability at 11*
ALL	2664	91.03 (44.94)	218.53 (26.24)	48.85 (14.80)
MEN	1378	92.29 (45.97)	217.55 (25.68)	47.24 (15.24)
WOMEN	1286	89.69 (43.79)	219.57 (26.80)	50.57 (14.11)
WNB	646	96.17 (49.66)	223.76 (28.80)	50.03 (14.71)
WB	640	83.14 (35.78)	215.34 (23.91)	51.11 (13.46)
WBSE (short/early)	101	83.89 (32.14)	214.71 (21.82)	51.98 (12.65)
WBSL (short/late)	191	92.14 (37.80)	226.47 (27.86)	55.35 (11.63)
WBLE (long/early)	253	75.15 (33.62)	206.35 (16.74)	46.66 (13.84)
WBLL (long/late)	95	85.50 (36.65)	217.59 (24.18)	53.48 (13.35)

Table 2.1 Means and standard deviations (in brackets) for deflated gross monthly earnings in the first job, age in months at which the first job started, and ability at age 11 scored out of 80

Samples	*ALL*	All individuals in the sample
	MEN	All men
	WOMEN	All women
	WNB	Women who experienced no breaks before age 33
	WB	Women who did experience a break before age 33
	WBSE	Women who experienced a short/early break (first break occurring before or at age 26, total time out of labour force by age 33 less than or equal to four years)
	WBSL	Women with a short/late break (after age 26, less than four years)
	WBLE	Women with a long/early break (before or at age 26, more than four years)
	WBLL	Women with a long/late break (after age 26, more than four years)

The figures presented in table 2.1 would appear to offer some preliminary support for the theory of human capital accumulation and interrupted work careers. For the 1286 women, those who do go on to experience an interruption before age 33 (*WB*) are, on average, observed as entering the labour market at an earlier age and with a lower starting salary than those women who experience no interruptions (*WNB*).[14] The sample of 640 women with an interruption are then divided into four groups according to the length and timing of their spells of non participation. By comparing the figures for those with short/early and short/late breaks, it may be seen that those who interrupted their career at an earlier age are associated with earlier entry into the labour market and lower initial earnings. Similar results are observed by comparing the two groups experiencing long/early and long/late breaks, where an interruption occurring at an earlier age appears to reduce both the time devoted to full time education and the starting salary. In addition to the timing of the break, the total amount of

[14] In performing the relevant *t*-test, the null hypothesis of equality between the mean starting salaries and entry dates for women with no breaks and those with future interruptions is rejected.

time spent out of the labour force would also appear to influence the entry date and starting salary in a way consistent with the theory. By comparing the figures given for women with short/early and long/early breaks (as well as those for short/late and long/late breaks), it may be seen that women experiencing relatively long interruptions enter the labour market earlier and with a correspondingly lower starting salary.[15] Overall, therefore, the figures in table 2.1 suggest that among the women who do experience interrupted careers, the duration of the break and it's timing within the life cycle does influence both the date at which individuals enter the labour market and earnings at the point of entry in the direction predicted by the theory.

The other notable feature of the figures presented in table 2.1 is that women who do not experience an interruption by age 33 (*WNB*) are seen as entering the labour market later and with a higher starting salary than men. In the model outlined in section 2, these two groups of individuals may be viewed as representing the continuous participation case and so may be expected to have similar patterns of human capital accumulation. One possible explanation for the difference in entry dates and starting salaries between these two groups rests in their levels of ability. It may be seen in the final column that women with no interruptions are observed as having higher ability at age 11 than males. Human capital theory predicts that among individuals planning similar levels of participation, those with higher ability will devote more time to full time education and therefore enter the labour market later and with higher earnings. Differences in the level of ability may also partly explain the differences in entry dates among the four groups of women who did experience an interruption in table 2.1. Although women with a long/early break are observed with an earlier entry date than those planning a short/late break, they are also observed as having lower ability. Any effect that non participation plans have on the decision to enter the labour market is then confounded with the independent effect that ability has on the investment decision. It then becomes necessary to use regression analysis in order to separately identify the effect that career plans have on the decision to cease full time education and enter the labour market for the first time. Table 2.2 below shows the importance of being able to adequately control for ability when assessing the effects of planned periods of non participation. For the combined sample of 2664 men and women, it may be seen that there is a general tendency for individuals within a higher ability group to enter the labour market at a later date and with a higher starting salary.

[15] With the exception of the mean starting salaries of women with short/late and long/late breaks, all of the differences in the mean starting salaries and entry dates across the four groups of intermittent participants described here are significant within the 5% level.

Ability score	*N*	*Starting salary (£)*	*Entry date (months)*
0-32	418	84.19 (45.36)	202.36 (11.98)
33-40	336	79.04 (44.04)	206.13 (18.08)
41-48	440	84.32 (37.97)	214.43 (23.38)
49-56	534	90.02 (42.32)	220.17 (26.37)
57-64	537	98.10 (49.32)	227.34 (27.92)
65-80	399	107.53 (43.53)	236.35 (27.35)

Table 2.2 Starting salary and entry dates according to levels of ability for men and women

2.5 Statistical framework and empirical findings

The main aim of this study is to assess the effect that future periods of non participation have on the starting salaries of female workers relative to males, who are assumed to have continuous participation throughout their working lives. It may be recalled from the previous theoretical discussion that the existence of career breaks is expected to lower the starting salary of females relative to otherwise comparable males. This arises as a result of women having a lower incentive to invest in human capital in each period leading up to the break and, therefore, entering the labour market earlier and with a lower stock of human capital. For those women who do experience an interruption, it was also shown how starting salary declines with the total length of the break and the earlier the break occurs in the life cycle. Section 5.1 outlines the statistical model used in order to test the empirical validity of these predictions. As in some of the studies reviewed in section 3, a two stage least squares approach is adopted where starting salary and years of future non participation are viewed as being simultaneously determined. The remaining parts of section 5 then present the results obtained from the estimation of the statistical model.

2.5.1 Statistical model

In the theoretical model described in section 2, it was seen how individuals will leave full time education and enter the labour market at the point where the optimal investment ratio falls marginally below the value one. Equation (2.8) implies that the date at which an intermittent participant enters the labour market for the first time, denoted by S, will be determined by ability (given by the parameters A and b), future career plans (given by g and L), and the other parameters of the model. It should be noted that (2.8) may also be used to give the entry date for continuous participants since for these individuals, the length of the break (L) is equal to zero. It is assumed that the other parameters of the model (T, r and δ) are the same for both continuous and intermittent participants. A statistical approximation for the equation representing the date of labour market entry for an individual may then be expressed as:

$$S_i = \alpha_1 + \alpha_2 ABILITY_i + \alpha_3 PARTICIPATION_i + \alpha_4 CTRL1_i + \varepsilon_{1i} \qquad (2.12)$$

where ε_{1i} is a random error term

In (2.12), *ABILITY* refers to the individual's level of ability at age 11 and *PARTICIPATION* includes a set of variables designed to capture the type of participation plans held by each individual. *CTRL1* refers to a set of additional control variables that are believed to have a possible influence on the date at which labour market entry occurs. The variables included in *CTRL1* are dummy variables capturing the social class of the cohort member's father when they were 11 years old.

In section 2.4, equation (2.11) was given for the starting salary of an individual which depends on the initial stock of human capital, the wage per unit of human capital, the date of entry (s), a productivity parameter (A), and the rate of depreciation. It is assumed that all of these factors are the same for individuals except the date of labour market entry. In the model, there are two measures of productivity- A and b. To keep the analysis as simple as possible it is assumed that individuals differ only with respect to b, which is interpreted as a measure of ability. The effect of this assumption is that differences in ability only appear in the equation determining entry dates and not the structural equation for initial earnings. The structural equation for starting salaries is given by (2.13) below. In this equation, the rate of return to schooling (A-δ) is constrained to be equal across individuals due to the assumption that individuals only differ with respect to b and not A.[16]

$$\ln Y_i = \alpha_5 + \alpha_6 S_i + \alpha_7 CTRL2_i + \varepsilon_{2i} \qquad (2.13)$$

where $\alpha_5 = wK_0$

$\alpha_6 = A - \delta$

ε_{2i} is a random error term

The variables included in *CTRL2* relate to the socio-economic group associated with the first job, establishment size, and whether the first firm is in the public sector or private sector.

[16] The parameter A could be interpreted as reflecting the efficiency of the education institution in producing units of human capital. Differences in the quality of schooling would then yield differential rates of return to schooling. This issue is explored in chapter 3 where an attempt is made to determine whether the quality of education affects earnings through the return to schooling.

These control variables are included in order to allow for differences in the starting salaries of individuals with identical entry dates that arise as a result of factors specific to the first firm that the individual works for. To analyse the effect that non participation plans have on starting salaries, it is possible to substitute (2.12) into (2.13) to obtain the following reduced form equation:

$$\ln Y_i = \beta_1 + \beta_2 ABILITY_i + \beta_3 PARTICIPATION_i + \beta_4 CTRL1_i + \beta_5 CTRL2_i + \mu_i \qquad (2.14)$$

where $\beta_1 = \alpha_5 + \alpha_6\alpha_1$ $\qquad \beta_5 = \alpha_7$

$\beta_2 = \alpha_6\alpha_2$ $\qquad \mu_i = \alpha_6\varepsilon_{1i} + \varepsilon_{2i}$

$\beta_3 = \alpha_6\alpha_3$

$\beta_4 = \alpha_6\alpha_4$

The estimation of equations (2.12) and (2.14) is the main way used in this study to test the empirical validity of the theoretical predictions outlined in section 2 concerning the effect that future career breaks have on the date of labour market entry and starting salaries of individuals. Several different versions of these equations are estimated which differ with respect to the variables contained within the *PARTICIPATION* term. In the first version of the equations, dummy variables are used to indicate whether the individual was a male (*MEN*), a woman with no interruptions prior to age 33 (*WNB*), or a woman who did experience an interruption to their career before age 33 (*WB*). The purpose of these initial estimations is to assess the effect that the existence of any type of career break has on the entry dates and starting salaries of women relative to those males and females who experience no such interruptions. Equations (2.12) and (2.14) are then re-estimated where the dummy variable capturing women with a break (*WB*) is replaced with four dummy variables indicating women with different types of interruption. The four sub groups identified are the same as those defined in table 2.1, where the interruptions are described as being either short/early, short/late, long/early, or long/late. Comparing the coefficients associated with these four dummy variables then allows an insight to be gained into the effect that the length of the break and it's timing has on both the date of labour market entry and initial earnings.

Following the estimation of equations (2.12) and (2.14) using dummy variables to capture career plans, the equations are re-estimated for the sample of women where the number of years of non participation (*NP*) is entered as a continuous variable. This specification enables the theoretical predictions relating to the length of the break to be tested since the coefficient associated with *NP* in each equation captures the effect that an additional year of non participation has on the date of entry and initial earnings respectively. Within this set up, the effects of the timing of the break are no longer explicitly modelled. When years of non participation is included as a continuous variable, it is not feasible to also include a continuous variable capturing the timing of the break because of a high degree of correlation between the two variables. This correlation arises since when analysing interruptions occurring before age 33, women who are observed as having accumulated a high number of years of non participation must have started taking time out of the labour market at a relatively early age.[17] For this reason, only the total number of years of non participation is entered as a continuous variable. The implication of this in the starting salary equation, given by (2.14), is that the coefficient associated with *NP* will incorporate both the effect that an additional year of non participation has on earnings along with any effect arising from the timing of the year of non participation. Women with a high value for *NP* in (2.14) may be observed with lower earnings as a result of experiencing a high number of years of non participation, and also as a result of taking their break early, but it is not possible to separately identify these two effects.[18]

When estimating equations (2.12) and (2.14) with the inclusion of *NP*, it is possible that the coefficients obtained are biased due to the potential endogeneity of years of non participation. It may be the case that instead of planned periods of non participation inducing female workers to enter the labour market with a lower starting salary, the causality runs in the opposite direction in that it is lower initial earnings that encourages future non participation. Under these circumstances, an additional equation may be written for the number of years of non participation as:

$$NP_i = \beta_6 + \beta_7 \ln Y_i + \beta_8 CTRL3_i + \varphi_i \tag{2.15}$$

Equations (2.14) and (2.15) form a simultaneous equation system with starting salary (*Y*) and years of non participation (*NP*) being the joint dependent variables. OLS estimation of (2.14) will generate biased coefficient estimates arising from the correlation between the error term and years of non participation. In order to obtain unbiased estimates of the coefficients in

[17] The correlation coefficient between years of non participation and the age at which the first break occurred was found to be -0.65.

[18] If data were available for the whole working life, it may be possible to incorporate measures of both the total quantity of non participation and the age at which the break started. This is because women with, for example, 10 years of non participation could be observed as starting their break over a large range of ages. With data from the NCDS only available up to age 33, however, women with a high value for *NP* must have started their non participation at a relatively young age. Higher values for *NP* will, therefore, also reflect interruptions occurring relatively early in the working life.

(2.14) and (2.15), a 2SLS approach is adopted. This involves estimating a reduced form for both starting salary and non participation where each of these joint dependent variables is regressed on all the exogenous variables in the system. Identification of the equations in the system comes about as a result of the control variables included in each of the equations. In (2.15) an additional set of control variables (*CTRL3*) are included that are not present in (2.14). These variables relate to partner's economic status, the number of children, and whether the individual owned their own home in 1991 (when they were 33 years of age).[19] After estimating the reduced form for years of non participation, the second stage of the 2SLS approach involves obtaining the predicted values of non participation and using these in (2.14) in place of the actual values for non participation. The predicted values of non participation will be uncorrelated with the error term asymptotically, and so OLS can be applied to re-estimate the structural equation for initial earnings. In a similar way, it would also be possible to estimate (2.15) using the predicted values obtained from the reduced form equation for starting salary in place of the actual values.

In addition to undertaking a 2SLS approach where starting salary and years of non participation are treated as the two joint dependent variable, it is also possible to follow a similar procedure where entry date and non participation are viewed as being the endogenous variables within the system. Equation (2.15) could be re-written with the date of labour market entry (*S*) included in place of initial earnings (*Y*). The interpretation of this is that earlier entry into the labour market may encourage future non participation, rather than in (2.12) where the causality runs in the opposite direction. A 2SLS treatment could then be undertaken for equations (2.12) and (2.15) where the joint dependent variables are the date of labour market entry and years of non participation.

2.5.2 Ordinary least squares estimates

The first set of results presented in this sub section arise from estimating the entry date and starting salary equations when each individual's level of future participation is captured by a dummy variable. Initially, the equations are estimated where individuals are classified as being either a male (*MEN*), a woman with no break before age 33 (*WNB*), or a woman with a break (*WB*). The variable *WB* simply captures whether or not a woman experienced any kind of interruption before age 33 and does not allow for any differences in either the length or

[19] It could be argued that not all of these variables are exogenous in the non participation equation, (2.15). In particular, the number of children could be the consequence of non participation rather than the cause. The validity of instruments is a common criticism of 2SLS estimation but is often unavoidable due to the availability of suitable variables.

timing of the break. Identifying individuals within these three broad categories enables some preliminary evidence to be presented concerning the influence that career breaks have on the investment decisions and starting salaries of females relative to continuous participants. The first column in table 2.3 below shows the results obtained from estimating equation (2.12) which relates the date of labour market entry to future participation, ability at age 11, and father's social class at age 11. The third column in table 2.3 then presents the OLS estimates of the starting salary equation, (2.14).

	Entry date equation (2.12) Dependent variable: *S* Coefficient (*t*-ratio)		**Starting salary equation (2.14)** Dependent variable: ln *Y* Coefficient (*t*-ratio)	
	(1)	(2)	(3)	(4)
FSC1	19.640 (11.058)	19.259 (10.877)	0.127 (3.924)	0.124 (3.835)
FSC2	13.222 (11.292)	12.811 (10.948)	0.088 (4.136)	0.084 (3.922)
FSC3	5.839 (3.792)	5.526 (3.594)	0.019 (0.678)	0.014 (0.504)
FSC5	-3.800 (2.634)	-3.701 (2.576)	-0.029 (1.100)	-0.028 (1.060)
FSC6	-3.377 (1.405)	-3.074 (1.284)	-0.010 (0.222)	-0.007 (0.154)
FSC7	0.334 (0.132)	0.013 (0.005)	-0.009 (0.207)	-0.012 (0.256)
ABILITY	0.647 (21.098)	0.634 (20.649)	0.002 (3.678)	0.002 (3.447)
SIZE2 (11-24)	-	-	0.047 (1.740)	0.050 (1.838)
SIZE3 (25-99)	-	-	0.136 (5.590)	0.138 (5.654)
SIZE4 (100-499)	-	-	0.144 (5.804)	0.146 (5.896)
SIZE5 (500+)	-	-	0.170 (6.476)	0.172 (6.570)
PRIVATE	-	-	-0.191 (10.079)	-0.190 (10.016)
SEG1	-	-	0.246 (7.214)	0.246 (7.212)
SEG2	-	-	0.168 (2.892)	0.168 (2.892)
SEG3	-	-	0.260 (10.043)	0.258 (9.943)
SEG5	-	-	-0.099 (3.816)	-0.100 (3.884)
SEG6	-	-	0.020 (0.785)	0.021 (0.818)
SEG7	-	-	0.174 (3.806)	0.173 (3.870)
WNB	3.565 (3.313)	3.619 (3.377)	-0.025 (1.191)	-0.025 (1.176)
WB	-4.592 (4.249)	-	-0.100 (4.681)	-
WBSE	-	-5.430 (2.349)	-	-0.089 (2.094)
WBSL	-	1.877 (1.076)	-	-0.058 (1.779)
WBLE	-	-8.800 (5.734)	-	-0.152 (5.187)
WBLL	-	-5.117 (2.148)	-	-0.057 (1.301)
constant	182.914 (114.357)	183.675 (114.659)	4.287 (101.068)	4.293 (101.150)
N	2664	2664	2664	2664
R-squared	0.271	0.278	0.221	0.223
F	109.81	85.07	37.50	32.97

Table 2.3 OLS estimation of equations (2.12) and (2.14) for the sample of 2664 males and females

Notes Being male (*MEN*) represents the excluded category of future participation
Variables *WNB* to *WBLL* are defined in the same way as in table 2.1
FSC1-7 relates to a father's social class, *SEG1-7* gives socio-economic group of first job
PRIVATE indicates first job was in a private firm, *SIZE1-5* gives establishment size
ABILITY is a measure of ability at age 11 and is scored out of 80
A full description of all the variables is provided in appendix A

By examining the results shown in column 1 of table 2.3, it may be seen that some support is found for the theoretical predictions concerning the effects that ability and future participation have on the date of labour market entry (which is defined as the age in months when the first job commenced). Individuals with higher ability at age 11 are found to enter the labour market significantly later implying that these individuals devote a greater proportion of their life to full time education. For women who do go on to experience any type of career break at some point before age 33 (*WB*), entry into the labour market occurs significantly earlier than comparable men (who represent the excluded case), and also women who do not experience any such interruptions (*WNB*).

Contrary to the predictions outlined in the theoretical section, it is also found that women with no breaks enter the labour market significantly later than similarly able males. In terms of the theory, similarly able males and females with continuous participation would be expected to enter the labour market at approximately the same time as a result of having similar investment profiles. If women with no interruptions to their careers enter the labour market later than men, it would then be expected that they would be associated with higher starting salaries. The results presented in column 3 of table 2.3, however, suggests that this is not the case since women with no interruptions to their careers (*WNB*) earn 2.5% less than males at the point of entry, although the effect is insignificant. One possible explanation for this result is the existence of discrimination which lowers the rate of return to education for females relative to males. It is then possible that women entering the labour market later, and with a greater stock of human capital, receive lower starting salaries than males. In order to investigate this, the structural equation for starting salary, given by (2.13), was estimated for each of the three groups identified in columns 1 and 3 of table 2.3. The results from these estimations revealed that the rates of return per year of schooling for males, women with no breaks, and women with breaks were 11.2%, 10.1% and 11.6% respectively. There is some evidence, therefore, that women planning strong labour force attachment receive lower starting salaries than males as a result of a lower rate of return to schooling. The observation that women planning career breaks are associated with the greatest rate of return, however, appears to suggest discrimination is not a key factor in explaining the difference in starting salaries between males and females.

The other important feature of the results given in the third column of table 2.3 is that women who do experience spells of non participation before they reach the age of 33 (*WB*) earn significantly less than comparable men at the point of entry. The coefficient associated with *WB* implies that women who experience a future break receive, on average, 9.5% lower starting salaries than males.[20] With respect to the other variables included in the estimation of (2.14), it may be seen that ability exerts a positive and significant effect on starting salaries. Both career plans and ability will influence initial earnings through their effect on entry dates, so in order to examine the role played by career plans in determining earnings it is necessary to control for ability. The results also imply that those working in the private sector (*PRIVATE*) and in establishments with fewer employees (captured by the *SIZE* variables) are associated with lower starting salaries for the same level of ability and participation plans. Those whose first job places them in a professional or non manual socio-economic grouping (*SEG1-SEG3*) are generally observed as having higher initial earnings than those within the manual socio-economic groups (*SEG5-SEG7*).[21]

The results shown in columns 1 and 3 of table 2.3, therefore, suggest that women who do interrupt their careers by the age of 33 are associated with earlier entry in to the labour market and lower starting salaries than comparable men and women with no interruptions. Following this result, equations (2.12) and (2.14) were re-estimated where the sample of women with a break was divided into four groups according to the total amount of time spent out of the labour force and the age at which the first interruption occurred. The results from these estimations are reported in columns 2 and 4 of table 2.3. For the entry date equation, it may be seen that three out of the four coefficients attached to the career break dummy variables have the expected negative sign and are statistically significant. Women classified as having a short/late break are found to enter the labour market later than men, although the effect is insignificant. In the starting salary equation, all of the coefficients have the anticipated sign although only two are significant. The largest pay penalty is observed for women experiencing a long/early break, where earnings are reduced by 14.1% relative to men. Women with a short/early break earn 8.5% less than males, although they do not earn significantly more than women with a long/early break.[22] This provides some evidence, therefore, for the hypothesis that longer interruptions lead to earlier entry in to the labour market and lower initial earnings. Among those with late breaks (*WBSL*, *WBLL*), however, there is little support for the prediction relating to the length of the break with both groups

[20] This figure is calculated as a result of interpreting the coefficient associated with a dummy variable in the usual manner i.e. taking the anti-log of the coefficient and subtracting one (Halvorsen and Palmquist, 1980).

[21] The SEG variables could be correlated with years of non participation if women planning career breaks enter certain occupational groups. In this case, part of the effect of non participation is captured by the SEG controls. Excluding the SEG controls was not found to substantially alter the results, although the magnitude of the coefficients associated with the career break dummies increased slightly.

[22] The test of equality between the *WBSE* and *WBLE* coefficients yields an F-statistic of 1.71, which has a p-value of 0.19.

earning around 5.5% less than men. The figures given in column 4 also provide some evidence that breaks occurring earlier in the life cycle have a greater detrimental effect on earnings, which may be seen by comparing the coefficient attached to *WBSE* with *WBSL*, and also *WBLE* with *WBLL*.

For the results presented in table 2.3, the entry date and starting salary equations were estimated using dummy variables capturing career plans in order to determine the effect that future interruptions have on the investment decisions of females relative to continuous participants. It was seen that, on average, women experiencing any kind of interruption were associated with earlier labour market entry and approximately 10% lower starting salaries than comparable men. By identifying different types of interruption, some evidence was also found to support the idea that longer breaks, or breaks occurring earlier in the life cycle have a greater negative influence on the human capital investment decision. Many studies looking at the effect of interrupted careers measure non participation as a continuous variable rather than as a dummy variable indicating whether or not the individual experienced time out of the labour force. Equations (2.12) and (2.14) were therefore re-estimated for the sample of 1286 women using the total number of years spent out of the labour force by age 33 (*NP*) as the measure of non participation instead of the dummy variables identified in table 2.3. This specification is also considered since it enables a conventional 2SLS technique to be employed where years of non participation is treated as a potentially endogenous variable. The results obtained from estimating (2.12) and (2.14) by OLS for women using years of non participation (*NP*) are reported in table 2.4 below.

Table 2.4 offers some additional empirical evidence relating to the theory of human capital and intermittent participation. The results presented in column 1 indicate that each additional year spent out of the labour market significantly lowers the age (measured in months) at which women first enter the labour market. This negative effect exists after controlling for the level of ability at age 11, which is in itself found to be a positive and highly significant determinant of the entry date. In terms of initial earnings, the figures in column 2 indicate that the number of years of non participation also exerts a significantly negative effect on female starting salaries. Each additional year spent out of the labour force is estimated to lower initial earnings by approximately 1%.[23] A woman experiencing a break with duration

[23] The two equations were also estimated with the inclusion of *NP*-squared along with *NP*. For the starting salary equation, the estimated coefficients (and *t*-ratios) for *NP* and *NP*-squared were -0.020 (2.285) and 0.001 (1.235). This is consistent with the theory since each year of non participation lowers the date of entry, but at a diminishing rate. This may be verified from the first and second derivatives of (2.8).

equal to the mean length of 4.89 years would therefore earn around 5% less than a woman with no interruptions at the point of entry.

	Entry date equation (2.12) Dependent variable: *S* Coefficient (*t*-ratio) (1)	**Starting salary equation (2.14)** Dependent variable: *lnY* Coefficient (*t*-ratio) (2)
FSC1	21.926 (8.588)	0.119 (2.722)
FSC2	13.395 (7.892)	0.080 (2.758)
FSC3	2.335 (1.018)	-0.008 (0.212)
FSC5	-3.880 (1.773)	-0.089 (2.403)
FSC6	-6.463 (1.833)	0.045 (0.760)
FSC0	-1.491 (0.429)	-0.075 (1.274)
ABILITY	0.605 (12.823)	0.002 (2.659)
SIZE2	-	0.096 (2.592)
SIZE3	-	0.158 (4.775)
SIZE4	-	0.194 (5.920)
SIZE5	-	0.224 (6.275)
PRIVATE	-	-0.209 (8.276)
SEG1	-	0.297 (5.089)
SEG2	-	0.118 (1.246)
SEG3	-	0.290 (8.756)
SEG5	-	0.084 (1.344)
SEG6	-	-0.061 (1.753)
SEG7	-	0.138 (0.800)
NP	-1.265 (6.637)	-0.010 (3.025)
constant	187.942 (73.699)	4.233 (76.070)
N	1286	1286
R-squared	0.2892	0.2951
F	64.94	27.90

Table 2.4 OLS estimation of the entry date and starting salary equations using the number of years of non participation (*NP*)

2.5.3 Two stage least squares estimates

As was discussed in the description of the statistical model, it may be inappropriate to treat the variable capturing years of non participation (*NP*) as exogenous. In addition to years of non participation exerting a negative effect on starting salaries, a feedback effect may exist in the sense that it is the realisation of lower initial earnings that encourages non participation. Under these circumstances, starting salary and years of non participation will represent the endogenous variables in a simultaneous equation system expressed by equations (2.14) and (2.15). The results presented in column 2 of table 2.4 relating to the estimation of the earnings equation (2.14) may then be biased due to the possible correlation between the error term and the variable *NP*. Unbiased coefficient estimates for the earnings equation may be obtained by estimating equation (2.14) by two stage least squares (2SLS).

The first stage in estimating equation (2.14) by 2SLS involves estimating a reduced form equation by OLS for the total number of years of non participation (*NP*). This reduced form involves regressing years of non participation on all the exogenous variables within the system. The regression will therefore include all of the three groups of control variables within (2.14) and (2.15) and also the measure of ability, but exclude initial earnings as an explanatory variable. Using the estimated coefficients obtained from this regression, predicted values for non participation are then computed which, in the second stage, are used in (2.14) instead of the actual values. The results from estimating this reduced form equation are given in the second column of table 2.5. Along with these results, column 1 of table 2.5 also displays the results obtained from estimating the structural equation for years of non participation, given by (2.15). When estimating this equation, the number of women in the sample falls from 1286 to 1281 due to missing observations for the set of explanatory variables denoted by *CTRL3*. These additional variables enable (2.15) to be identified and relate to the economic status of the woman's partner, the number of children and whether the individual was a homeowner at age 33.

The most notable feature of the results shown in the first column of table 2.5 is that the coefficient associated with initial earnings (*LNY*) in the structural equation for non participation is negative and significant. This implies that women with higher initial earnings experience fewer years out of the labour force. Finding a negative coefficient in this regression provides further evidence for the possible simultaneity between starting salaries and participation plans and the need to estimate the model using a 2SLS approach. With respect to the other explanatory variables, it is found that women with partners who are not in employment at age 33 (*UPPART* and *OTHPART*) are observed as having accumulated a greater quantity of non participation.[24] Being a homeowner at age 33 (*OWNHOME*) is also found to significantly lower the number of years spent out of the labour force. As would be anticipated, the number of children that each woman has by the age of 33 (*CHILD*) significantly increases the number of years spent out of the labour force by age 33.[25]

[24] The excluded category relates to no partner present in 1991, or no data available concerning the partner's economic status.
[25] This structural equation for non participation was also estimated with the inclusion of the ability measure, but was found to have little effect on the results shown in column 1.

Control	Variable	**Equation (2.15)** Coefficient (*t*-ratio) (1)	**Reduced form for *NP*** Coefficient (*t*-ratio) (2)
	LNY	-0.801 (4.718)	
CTRL3	*FTPART*	0.033 (0.145)	-0.031 (0.136)
	PTPART	-0.961 (1.392)	-0.903 (1.306)
	UPPART	1.768 (3.474)	1.587 (3.094)
	OTHPART	1.253 (1.999)	1.114 (1.775)
	OWNHOME	-0.603 (3.500)	-0.611 (3.481)
	CHILD	1.509 (8.590)	1.501 (8.521)
	CHILDSQ	0.037 (0.756)	0.040 (0.802)
CTRL2	*SIZE2*	-	0.320 (1.216)
	SIZE3	-	0.303 (1.289)
	SIZE4	-	0.092 (0.394)
	SIZE5	-	0.360 (1.418)
	PRIVATE	-	0.284 (1.583)
	SEG1	-	-0.874 (2.067)
	SEG2	-	-1.325 (1.966)
	SEG3	-	-0.860 (3.670)
	SEG5	-	0.561 (1.258)
	SEG6	-	0.158 (0.637)
	SEG7	-	-1.517 (1.233)
CTRL1	*FSC1*	-	-0.067 (0.215)
	FSC2	-	0.029 (0.142)
	FSC3	-	0.172 (0.625)
	FSC5	-	0.851 (3.236)
	FSC6	-	-0.355 (0.835)
	FSC0	-	-0.365 (0.868)
	ABILITY	-	0.005 (0.878)
	constant	3.947 (5.053)	-0.102 (0.234)
N		1281	1281
R-squared		0.3459	0.3617
F		84.08	28.44

Table 2.5 OLS estimates for the structural and reduced form non participation equations

Notes *LNY* equals deflated gross monthly pay in the first job
FTPART indicates partner at age 33 working full time
PTPART indicates partner at age 33 working part time
UPPART indicates partner at age 33 unemployed
OTHPART indicates partner's economic status described as 'other'
OWNHOME equals one if individual owned their own home in 1991
CHILD and *CHILDSQ* equals the number of children and the number of children squared by the age of 33

Column 2 of table 2.5 relates to the reduced form equation where years of non participation is regressed on all the exogenous variables in the system. These coefficient estimates are used to compute the predicted values of non participation for the sample of women, which are then included in the starting salary equation in place of the actual values. The results obtained from estimating the earnings equation (2.14) by 2SLS are then shown in the second column of table 2.6.

	Dependent variable: ***ln S*** Coefficient (*t*-ratio) (1)	**Dependent variable:** ***lnY*** Coefficient (*t*-ratio) (2)
FSC1	21.569 (8.369)	0.119 (2.697)
FSC2	13.175 (7.709)	0.080 (2.749)
FSC3	2.338 (1.018)	-0.009 (0.241)
FSC5	-3.485 (1.574)	-0.095 (2.550)
FSC6	-6.551 (1.856)	0.045 (0.750)
FSC0	-1.610 (0.462)	-0.076 (1.284)
ABILITY	0.596 (12.475)	0.002 (2.593)
SIZE2	-	0.095 (2.573)
SIZE3	-	0.160 (4.807)
SIZE4	-	0.194 (5.896)
SIZE5	-	0.223 (6.230)
PRIVATE	-	-0.211 (8.327)
SEG1	-	0.312 (5.215)
SEG2	-	0.120 (1.266)
SEG3	-	0.291 (8.679)
SEG5	-	0.084 (1.336)
SEG6	-	-0.062 (1.766)
SEG7	-	0.138 (0.801)
NP (predicted)	-1.584 (4.682)	-0.009 (1.473)
constant	189.211 (68.769)	4.234 (73.789)
N	1281	1281
R-squared	0.2864	0.2959
F	61.58	27.54

Table 2.6 Two stage least squares estimates for the entry date and starting salary equations

In estimating (2.14) by 2SLS it may be seen that each additional year of future non participation lowers initial earnings by around 1%. The magnitude of this effect is therefore the same as that which was found when the equation was estimated by OLS (table 2.4, column 2), but is insignificant within the 10% level. For the remaining explanatory variables in the second column of table 2.6, the estimated effects on earnings are found to be similar in terms of magnitude and significance to the initial OLS estimates.

For the 2SLS results reported in table 2.6, the predicted values for years of non participation were obtained by estimating a reduced form equation by OLS (table 2.5, column 2). It may be inappropriate, however, to estimate equations with non participation as the dependent variable by OLS since there are a large number of individuals with zero years of non participation. Out of the sample of 1286 women, 646 are observed as having experienced no interruptions for child raising purposes by the age of 33. In terms of the basic labour supply model, some of these women may have a desired level of non participation that is negative, in which case they would be constrained to a solution involving zero years of non participation, which is the value observed within the data. Given data which may be censored in this way, it may be more appropriate to estimate the reduced form equation for non participation as a tobit model rather than by OLS. The predicted values for non participation obtained from such a model may then be used in the estimation of the starting salary equation. In doing this, the coefficient associated with years of non participation was estimated to be -0.005 with a *t*-ratio of 1.906.[26]

In examining the effects of interrupted careers, an OLS regression was also run in section 5.2 to examine the effect that future non participation had on the date of labour market entry (table 2.4, column 1). The first column of table 2.6 presents the results from estimating this entry date equation by 2SLS. In the same way that starting salaries and participation plans may be simultaneously determined, it is also possible to consider entry dates and participation plans as the endogenous variables within a simultaneous equation system. Equation (2.12) shows how the date of labour market is related to future levels of non participation, but in a similar way to (2.15), years of non participation may be partly determined by the date of labour market entry instead of initial earnings. In this case, another reduced form equation for years of non participation may be estimated which is then used to compute predicted values for non participation.[27] These predicted values may then be used in place of the actual values in the structural equation (2.12) that has the date of labour market entry as the dependent variable. The results from estimating this equation are shown in table 2.6, column 1. The coefficient associated with *NP* implies that after controlling for ability, years of non participation exerts a negative and significant effect on the date at which women first enter the labour market. Each additional year of non participation lowers the age at which labour market entry occurs by 1.6 months.[28]

Overall, the 2SLS results presented in this section suggest that after allowing for the potential simultaneity between the two variables, years of non participation exerts a negative effect on starting salaries. Each additional year spent out of the labour force is found to reduce initial

[26] The significance of this coefficient, however, is unclear since the estimation procedure involving the tobit reduced form does not generate the correct standard errors at the second stage.

[27] This reduced form for non participation will have the same explanatory variables as that of table 2.5, column 2, except for the variables contained within *CTRL2* since these control variables are viewed as only influencing earnings within the first job.

[28] The entry date equation was also estimated when the predicted values of non participation were obtained from a tobit model. The coefficient for *NP* was estimated to be -0.780 with a *t*-ratio of 4.669.

earnings by approximately 1%, although the effect is statistically insignificant. Slightly stronger evidence, however, is found to exist for the relationship between non participation and the date of labour market entry. Although these two variables may also be jointly dependent, 2SLS estimation reveals that each year of non participation lowers the date of entry by 1.6 months with the effect being highly significant.

2.6 Conclusion

This study has attempted to find empirical evidence in support of the theoretical predictions offered by the life cycle human capital framework regarding the effect that anticipated spells of non participation have on the investment incentives of women. It may be shown that individuals planning intermittent participation in the labour market will invest in less human capital in each period prior to the break occurring than similarly able individuals planning continuous participation. When looking at individuals over the complete life cycle, an implication of this is that intermittent participants will devote fewer years of their lives to full time education and, therefore, enter the labour market earlier. With less human capital having been accumulated at the point of entry, women planning career breaks would then be expected to receive lower earnings in their first job. It is also possible to show that the negative influence that non participation has on entry dates and starting salaries increases with the duration of the break and the earlier it occurs within the life cycle.

The statistical analysis undertaken using a sample of individuals taken from the NCDS provided some evidence to support the negative relationship between non participation and human capital investment. In the most basic version of the statistical model considered, it was found that women experiencing any kind of interruption by the age of 33 entered the labour market at a significantly earlier date and with a 10% lower starting salary than men of similar ability. Relative to women with no interruptions, these intermittent participants received approximately 7.5% less pay in their first job. When the sample of women with an interruption was then divided into four groups according to the type of break experienced, some evidence was also found to support the idea that long periods of non participation occurring early in the life cycle exerted the greatest negative effect on the date of entry and initial earnings. Throughout the initial estimations it was found that women with no interruptions were associated with earnings that were, on average, 2.5% less than men, but entered the labour market at a significantly later date. This result could be consistent with a signalling hypothesis in that women planning a strong attachment to the labour market signal their intentions to potential employers by investing in an additional quantity of human capital that is not formally rewarded at the point of entry.

The entry date and starting salary equations were also estimated for females where future career plans were captured by the total number of years of non participation accumulated by age 33. OLS estimation of these equations showed that each year spent out of the labour force induced significantly earlier entry into the labour market and also lowered initial earnings by 1%. Including non participation as a continuous variable enables a conventional two stage least squares procedure to be undertaken with starting salary and non participation as the joint dependent variables. The results from the 2SLS estimation also found that each year of non participation lowered initial earnings by 1%, although the effect was no longer significant. A significantly negative relationship, however, was found to exist between years of non participation and the date of labour market entry when the entry date equation was estimated using a similar 2SLS technique.

One of the main findings throughout the empirical analysis is that it would appear that the evidence concerning the relationship between career breaks and entry dates is more convincing than that between career breaks and starting salaries. The coefficients associated with the non participation variables in the entry date equation have a tendency to have greater *t*-ratios than those in the starting salary equation. The model predicts that those anticipating career breaks will enter the labour market earlier, which will in turn, lead to a lower starting salary. The evidence, however, would appear to be stronger regarding the first link in the chain. One of the possible reasons for why the evidence concerning the subsequent relationship between non participation and initial earnings is weaker lies in the use of the control variables (*CTRL2*) included in the starting salary equation, (2.14). If intermittent participants, who enter the labour market earlier, are more inclined to work in smaller firms or private sector firms, then they may be expected to have lower earnings as a result of opting to work in these types of firm. When estimating the starting salary equation with the inclusion of control variables capturing the characteristics of the firm, part of the total impact of non participation then becomes embodied within these additional controls. This may mean that in the estimation of the starting salary equation given by (2.14), the overall effect of non participation is being understated. By estimating the earnings equation without these controls, the coefficient associated with non participation will capture the effect that those planning to interrupt their careers tend to work in smaller firms, in addition to the fact that such workers enter the labour market with a lower human capital stock. In estimating the equation without the controls for the characteristics of the firm, the coefficient associated with non participation increased in terms of magnitude and significance, but the explanatory power of the model was reduced considerably.[29]

It is also possible that the estimated effects that career breaks have on entry dates and starting salaries is understated because of the way that women who experience interrupted careers are defined. The most recent data available from the NCDS refers to individuals when they were 33 years of age. In the empirical analysis within this study, a woman was defined has having experienced a career interruption if they reported having spent time out of the labour force for child raising purposes by the time they were 33. Women who did not report any spells of non participation before age 33 are defined as representing the continuous participation case. It is likely, however, that among the sample of women who experienced no interruptions before age 33, many would have gone on to experience a break at a later age. Comparing the starting salaries of women who did experience a break with those who did not may then lead to an underestimate of the effect that non participation has on earnings being obtained. This is because among the group of women considered as having continuous participation, there will be some women who experience breaks that are yet to observed. The presence of women who do go on to experience a break among the group of continuous participants will lower the mean starting wage of continuous participants, which will in turn lead to the estimated effect that career breaks have on starting salaries being understated. This limitation could be overcome if data concerning an individual's level of participation was available in each year leading up to the date of retirement.

[29] Estimating (2.14) without the controls relating to socio-economic group, establishment size and private sector (i.e. *CTRL2*), the coefficient (and *t*-ratio) attached to *NP* became -0.02 (4.705). This compares to -0.01 (3.025) in table 2.4, column 2. The R-squared of the model, however, falls from 0.295 to 0.111.

Chapter 3 Rates of Return to Schooling and the Quality of Education in England And Wales

3.1 Introduction

The quality of education received by pupils during their years of schooling has become one of the key political issues in the UK over the last decade. The Labour government came to power in 1997 with a commitment to raising standards within the education system. In July 2000, as part of a three year public spending review, the government announced that schools, colleges and universities would receive an additional £12 billion in the years leading up to 2004. This injection of funds is anticipated to raise education spending in real terms by 6.6% per year in the four year period stretching to 2004. Some of the benefits of the policy are also expected to be felt in the short term with a typical secondary school in England seeing its direct funding from central government increase by £20,000 in the financial year 2001-02. Along with this increase in funding, however, the government has set new educational attainment targets to be met by the Department for Education and Employment. By the year 2004, at least 38% of pupils in all Local Education Authorities should obtain a minimum of five GCSE qualifications at grades A*-C.[1] This recent policy announcement would therefore appear to be based on a belief that increased funding raises the quality of education received by pupils, enabling them to achieve superior results in the exams that accompany the end of compulsory schooling. Higher educational attainment may then be expected to improve the position of individuals in the labour market, either in terms of raising the probability of finding suitable employment, or increasing potential earnings. This chapter attempts to assess the likely effectiveness of the recent government policy proposal by looking at past experience within England and Wales. Data from the National Child Development Study (NCDS) is used to determine whether individuals who received higher quality secondary education in the 1970s are associated with higher earnings twenty years later. Finding evidence for a link between the quality of education and earnings would suggest that directing more resources to schools may be an effective policy for improving the labour market status of individuals.

Economic studies of school quality have tended to concentrate on the effects that variables such as the number of pupils per teacher and expenditure per pupil have on earnings in the labour market. The manner in which quality is believed to affect earnings, however, is an area of debate. One of the most established findings from research undertaken within many countries is the existence of positive rates of return to schooling. These studies offer estimates

[1] These figures were reported in the *Financial Times*, July 19th 2000.

of the average rate of return for all individuals included within the relevant sample. It is possible, however, that individuals receiving high quality education earn a rate of return above the average. The first approach for analysing the effects of quality, therefore, hypothesises that quality increases the value of each additional year of schooling, creating a steeper earnings-schooling profile. An alternative approach incorporates the measures of quality as additional explanatory variables within a standard wage equation. In this framework, higher quality shifts the earnings-schooling profile upward. Both of these approaches have been applied to US data to provide evidence for the existence of relatively strong quality effects. Recent studies in the UK by Dearden *et al* (1998) and Harmon and Walker (2000) have followed the second approach for the NCDS cohort. The results from these studies have not detected any significant wage effects associated with the quality of education received. The statistical analysis presented in this study also uses the NCDS as its primary source of data but examines the evidence for the alternative methodology, where quality affects earnings through the rate of return to schooling.

In order to test the hypothesis that the quality of education systematically affects the return to schooling, an empirical methodology is adopted that is essentially a simplified version of Card and Krueger's (1992) two stage regression approach. For the first stage, the NCDS data is used to estimate a conventional earnings equation for individuals aged 33, but where separate estimates of the return to schooling are obtained for each of the LEAs in England and Wales in which the cohort members could have been educated. The second stage then involves regressing these estimated returns on a set of variables relating to the average quality of education within each of the LEAs. An attempt is also made within the second stage to control for other factors which may influence the return to schooling, such as whether the LEA segregates pupils according to ability and the average income of parents within the LEA. The results obtained from estimating the first stage by OLS suggest that there is considerable variation in the returns to education across LEAs, ranging from 6.3% to 18.5%. In the second stage of the statistical analysis, the standard measures of quality, such as the pupil-teacher ratio, teacher salary, and expenditure per pupil are found to exert no significant effects on the LEA-specific returns obtained from the first stage. Some evidence is found, however, to support the idea that segregating students according to their ability is beneficial to all students since LEAs practicing selection are found to have a higher return to schooling.

In the remaining sections of this chapter, section 2 presents a review of some of the existing literature relating to the effects of school quality that have been undertaken using US and UK data. This review is organised according to the different types of empirical methodology used. The third section outlines the two stage statistical model used to assess the effect that quality has on the return to schooling in England and Wales. It is in this section where consideration is given to the literature surrounding the various biases that may exist in conventional OLS estimates of the return to schooling. The fourth section of the chapter then offers a detailed description of the data used within the empirical analysis. Section 5 begins by obtaining an OLS estimate of the average rate of return to schooling for the sample of individuals taken from the NCDS. This estimate is found to be around 11%, which is higher than the estimates obtained by Dearden (1999b). After an attempt is made to correct for the biases associated with unobserved ability, endogeneity and measurement error, this estimate is found to remain at approximately 11%. Given that these biases appear to offset each other, conventional OLS is then used in section 5.2 to estimate the equation for deriving the LEA-specific returns to schooling. The remaining parts of section 5 then present the results obtained from estimating the second stage of the statistical analysis and some additional estimations, while section 6 discusses some of the conclusions that may be drawn from the study.

3.2 Empirical approaches for analysing the effects of school quality

The effect that school quality has on an individual's educational performance and subsequent earnings is not a new area of study within labour economics. It is a subject, however, that has been revisited in recent years, particularly in the US where the existence of large panel data sets enables individuals to be tracked from the time of their schooling to dates later in their working lives. With such data it becomes possible to assess the effects that the quality of education received by an individual has on their earnings in the labour market. Fewer studies of the effects of quality exist in the UK, partly because there are fewer sources of data on earnings and school quality that can be matched together. The purpose of this section is to review some of the existing studies within the empirical literature according to the methodology adopted. In some studies, quality is hypothesised as altering the intercept of the earnings-schooling relationship, while in others, it is believed to influence the rate of return to schooling. A third group of studies model school quality as affecting both the intercept and the rate of return to schooling in the earnings equation. The results obtained from some of the studies within each of these three approaches are presented below. Another important distinction between the different studies is the level of aggregation of the quality data. In some cases, quality is measured as a regional average, while in others, school-specific measures of quality are included. As will be discussed below, both of these methods for capturing quality may introduce a source of bias into the analysis.

3.2.1 Approach 1: Quality affects the intercept of the earnings-schooling profile

An example of some of the early work analysing the effects of school quality is by Rizzuto and Wachtel (1979). Using both 1960 and 1970 US Census of population data, they estimate a conventional earnings function for each of the two Census years that includes an additional term representing a measure of quality. The equation estimated is expressed as:

$$\ln Y = \alpha_0 + \alpha_1 EXP + \alpha_2 EXP^2 + \alpha_3 \ln WEEKS + \alpha_4 S + \alpha_5 \ln Q + \alpha_6 URBAN + \mu \qquad (3.1)$$

In this equation, the log of annual earnings is regressed on years of labour market experience and its square, the log of the number of weeks worked a year, the number of years of schooling (*S*), a dummy variable indicating urban residence, and a quality variable (*Q*) entered in logs. The main measure of quality used was annual expenditure per elementary school pupil. This expenditure measure was obtained for each state and for six different time periods in which the individuals in the sample could have attended school. A relevant figure was then assigned to each individual according to their state of birth and their age.[2] The results from estimating (3.1) suggested that the rate of return to schooling for white males was between 7% and 8%. Since the expenditure measure is entered in logs, the coefficient obtained may be interpreted as an elasticity, which was found to be significantly positive and range from 0.08 to 0.11 for white males. Rizzuto and Wachtel then re-estimated (3.1) with the inclusion of additional variables capturing school quality at the state level. Average teacher salary and the length of the school year were both associated with significantly positive effects, but the effect of the teacher-pupil ratio was less conclusive. Overall, therefore, Rizzuto and Wachtel find quite strong evidence for the existence of quality effects using the specification suggested by (3.1) and incorporating state-level measures of quality.

Two recent studies in the UK by Dolton and Vignoles (1996) and Harmon and Walker (2000) have estimated an equation similar to that of (3.1) in order to assess the effect that quality has on the earnings of a sample of 33 year old males taken from the NCDS. Both of these contributions included measures of quality relating to the actual school that the individual attended as well as measures based on the average for all secondary schools within the individual's LEA.[3] The results obtained by Harmon and Walker suggested that the rate of return to non-compulsory education was approximately 5%, but no evidence was found for the existence of quality effects. None of the coefficients associated with any of the quality measures, such as expenditure per pupil and teacher salary, were found to be statistically

[2] A common assumption in many US studies is that individuals are educated in their state of birth.
[3] The school-specific quality measures were taken from the NCDS, while the LEA-specific measures were obtained from The Chartered Institute of Public Finance and Accountancy (CIPFA).

significant.[4] Dolton and Vignoles also find that such measures of quality, along with the pupil-teacher ratio, have no significant influence on earnings when estimating a similar equation that includes additional controls for peer group effects, which is measured by the proportion of pupils in the cohort member's class whose father was employed in a non manual occupation.[5]

Dearden *et al* (1998) also use the NCDS to estimate the effect that school quality has on an individual's earnings in an equation similar to that of (3.1) above. One of the advantages of the NCDS is that it contains detailed information on family background and local neighbourhood characteristics. Dearden *et al* make use of these variables to correct for potential sources of bias associated with the estimated quality effects. For example, it could be the case that parents who show a strong interest in their child's education may select schools of higher quality, and such interest may also lead to higher earnings through other channels. Under these circumstances, the omission of family background variables in an equation like (3.1) could generate an upward bias in the estimated quality effects. Another source of bias may arise from the level of deprivation within the area. LEAs with a high level of deprivation tend to receive more funding from central government and so potentially have higher expenditure per pupil. If it were the case that pupils living in deprived areas were also associated with lower educational performance, there may exist a downward bias in the estimated quality effects since LEAs with higher expenditure may be observed as having lower educational performance.

Dearden *et al* estimate equations for earnings at ages 23 and 33 where measures of quality are included as additional explanatory variables along with sets of variables relating to family background and neighbourhood characteristics. In estimating these equations for both males and females, it was generally found that the quality variables exerted no significant effect on earnings. The only significant quality effect in both of the male equations was the average salary of secondary school teachers in 1974, which exerted the expected positive effect. No significant effects were found for expenditure per pupil, pupil-teacher ratios, or single sex schools.[6] Males who attended either a grammar school or a private school were found to have significantly higher earnings at age 33. Controlling for school type may be important since

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[4] The UK studies mentioned here differ from equation (3.1) in that the quality measures are not entered in logs, include variables controlling for ability and have a different set of other explanatory variables.
[5] Dolton and Vignoles also include class sizes at age 11 (which are likely to be correlated with the pupil-teacher ratio), but these variables were found to have no significant effect on wages.
[6] As in Harmon and Walker's study, Dearden *et al* use a combination of NCDS school-specific measures of quality and CIPFA LEA-specific measures. As discussed by Moulton (1990), however, including aggregated variables such as LEA-specific measures of quality into an individual level wage equation may create an additional source of bias in the estimated coefficients.

grammar schools generally take the more able students and so for a given level of quality, individuals who attended a selective school may be associated with higher earnings. In contrast, no evidence was found in the female equations for significant wage effects associated with the type of school attended.

3.2.2 Approach 2: Quality affects both the intercept and slope of the earnings-schooling profile

The studies summarised in section 2.1 estimate an earnings equation of the form given by (3.1). In this specification, measures of school quality are hypothesised as influencing earnings for any given level of schooling. Higher quality is therefore believed to lead to an upward shift in the earnings-schooling schedule. It is also possible, however, that in addition to shifting the profile, quality also affects the slope of the earnings-schooling relationship. It may well be the case that individuals attending higher quality schools receive a greater return for each year that they devote to full time education. An example of a study that incorporates both of these quality effects is that by Betts (1995). Using data from the National Longitudinal Survey of Youth, Betts estimates an equation of the following form where school-level measures of quality (Q) are entered separately and as interactions with years of schooling (S):

$$\ln y_{ist} = \alpha + \beta X_{ist} + \rho S_{ist} + \theta Q_{ist} + \tau (Q_{ist} \times S_{ist}) \qquad (3.2)$$

Included in the set of quality variables are the starting salary of teachers, the percentage of teachers with a Masters degree or higher, and the teacher-pupil ratio. One of the main differences between Betts' study and that of many others is the use of quality measures that relate to the actual school attended rather than regional averages. Betts argues that the use of school-specific measures eliminates errors arising from individuals not being educated in their state of birth and removes the possibility of aggregation bias. In estimating various versions of (3.2), however, no significant quality effects were detected, either operating through the intercept or through the rate of return to schooling.

Altonji and Dunn (1996) also examine the effect that school-specific quality measures have on both wage levels and rates of return to education by looking at differences in quality among siblings. One of the common sources of bias in the empirical estimates of quality effects arises from unobserved family characteristics. Certain family characteristics that raise earnings may also be positively correlated with measures of school quality, which generates an upward bias in the estimated quality effects. This source of bias may be reduced when looking at differences in earnings and quality among siblings since these individuals possess the same family background characteristics. Using data from the National Longitudinal Surveys, Altonji and Dunn estimate an equation for each individual that relates the deviation of their earnings from the mean value for their family, to deviations from the family means of years of schooling, the school-specific quality measures, and the other explanatory variables.[7] This equation is estimated for a pooled sample of males and females containing approximately 300 siblings who differ with respect to their quality variables, i.e. have deviations from the family mean that are non zero. The equation is estimated four times since only one measure of school quality is included at a time. The results obtained from these estimations showed that teacher salary exerted a significantly positive wage level effect, and a significantly negative interaction effect. Higher teacher salary, therefore, would appear to increase earnings, but this effect declines with the number of years of schooling accumulated. Significant effects were also found to exist for a quality index given in the NLS data. Expenditure per pupil and the student-teacher ratio were both found to exert positive wage level effects, although only significantly so for expenditure per pupil.[8] Altonji and Dunn's work therefore provides relatively strong evidence for the existence of quality effects when examining differences among siblings who possess similar family characteristics.

3.2.3 Approach 3: Quality affects the rate of return to schooling

One of the most commonly referred to studies within the quality literature is by Card and Krueger (1992). In their work, school quality is modelled as influencing the rate of return to education, but unlike the studies described in section 2.2, Card and Krueger use a two stage procedure to estimate the quality effects. The first stage of their analysis involves estimating the following earnings equation using 1980 US Census data for three separate cohorts, identified by the decade in which they were born:

$$y_{ijk} = \delta_j + \mu_k + X_{ijk}\beta + S_{ijk}(\gamma_j + \rho_r) + \varepsilon_{ijk} \tag{3.3}$$

In this equation, the log of weekly earnings of individual i, born in state j, and currently residing in state k of region r is related to a fixed effect for their state of birth (δ_j), a fixed effect for their state of residence (μ_k), a set of explanatory variables (X_{ijk}), and years of education (S_{ijk}). The most notable feature of (3.3) is that the return to years of education has two separate components. The first component relates to the state of birth, where it is assumed

[7] Altonji and Dunn investigate whether the observed differences in school quality between siblings are related to differences in other observable factors or family circumstances, but find no evidence to support this possibility.

[8] The interaction effects on these two variables were both insignificant.

that the individual is also educated, and is denoted by γ_j. The second part of the return to education is specific to the region (of which there are nine) in which the individual currently resides and is denoted by ρ_r. Within this framework, the state of birth specific returns to education (γ_j) are identified by observing two or more individuals currently residing in the same region, but who were educated in different states. Similarly, region of residence specific returns (ρ_r) may be estimated from individuals educated in the same state, but who live in different regions. If everybody remained in the state in which they were educated, it would not be possible to identify these two separate components that contribute to the rate of return to education. Card and Krueger attempt to determine whether the returns to education attributable to the state of birth (i.e. the γ_j coefficients) may be explained by the variation in school quality across states. In order to do this, they estimate the following second stage equation where the dependent variable consists of the estimated state of birth specific returns to education obtained from the first stage. The dependent variable consists of 147 estimated returns since there are 49 possible states of birth and equation (3.3) is estimated for each of the three cohorts.

$$\gamma_{jc} = a_j + \alpha_c + Q_{jc}b \tag{3.4}$$

where γ_{jc} is the state of birth specific return for those educated in state j and from cohort c

Q_{jc} is a vector of quality measures in state j for when cohort c attended school

a_j is a permanent fixed effect for state j (not varying across cohorts)

α_c is a fixed effect for cohort c

c represents the birth cohort, either 1920-29, 1930-39, or 1940-49

In equation (3.4), state of birth fixed effects are included to capture any permanent differences in rates of return arising from differences in, for example, distributions of ability across states. The measures of quality included relate to the pupil-teacher ratio, length of term, and teacher salary. These variables are entered as state averages reflecting the level of quality that existed within each of the 49 states at the time when each of the three birth cohorts would have attended school.

In estimating the first stage, Card and Krueger found that the rates of return across states of birth averaged 7.4% for the youngest cohort and 5.1% for the oldest. Various versions of the second stage were estimated where the quality measures were entered individually and collectively.[9] In addition, Card and Krueger experimented by running the second stage

[9] The second stage was estimated by weighted least squares using the inverse sampling variances of the estimated rates of return obtained from (3.3) as the weights.

regression with and without the 49 state effects. For the estimations that excluded the state fixed effects, all of the three quality variables were found to have the expected sign and were statistically significant when entered individually. When entered collectively, however, only relative teacher salary remained highly significant. Similar results were obtained for the estimates that included the state effects in that all of the quality measures were significant when entered individually, but when all three measures were included, only the pupil-teacher ratio and teacher salary had significant effects acting in the anticipated direction.[10] The results from this regression implied that a reduction in the pupil-teacher ratio by 10 students raises the rate of return to education by 0.9%, while a 30% increase in teacher salary raises the rate of return by 0.3%. Finally, Card and Krueger re-estimated the second stage with the inclusion of some additional family background variables. It could be the case that such family variables are correlated with quality and vary across birth cohorts within each state, meaning that they are not fully captured by the state specific effects. The estimated quality effects are then potentially biased by a failure to control for family background effects. By including variables relating to the state averages of parents' education and per capita income for the time that each cohort attended school, however, little alteration in the estimated quality effects was observed.

3.3 Empirical methodology

The empirical studies referred to in the previous section suggest that there are a number of alternative approaches for looking at the way school quality affects earnings. The two existing UK studies that use the NCDS follow the approach where quality is envisaged as influencing the intercept term within the earnings equation. The empirical analysis presented in this study also relies on the NCDS for its main source of data, but uses an approach that is essentially a simplified version of Card and Krueger's two stage methodology. In the first stage of the statistical analysis, estimates of the rate of return to education are obtained for each of the Local Education Authorities (LEAs) in England and Wales. The second stage then involves regressing these estimated rates of return on variables capturing the level of quality within each LEA. Unlike the existing UK studies, therefore, where quality affects the intercept of the earnings-schooling relationship, this two stage approach hypothesises that quality raises the slope of the earnings-schooling profile. The present study also differs from previous UK work in that all of the measures of quality included in the second stage refer to average values within each LEA. The studies by Dearden *et al* (1998) and Harmon and Walker (2000)

[10] In the model with state fixed effects, term length exerted a negative effect on the rate of return, but was insignificant in the regression including all three quality measures.

include a mixture of both school-specific and LEA-specific measures of quality when estimating their wage equations.

The purpose of this section is to provide a detailed description of the two stage statistical approach used to analyse the effect of school quality on earnings. Since the first step involves estimating the rate of return for each of the LEAs, this part of the analysis shares much in common with the extensive literature that already exists on estimating the returns to schooling. Some attention is therefore given in section 3.1 to describing some of the relevant estimation issues raised within this literature. Although the focus of the present study is concerned with the effects of quality, it may be important to obtain reliable estimates of the rates of return to education in the LEAs since these estimates are carried over into the second stage of the analysis.

3.3.1 Issues relating to the estimation of the return to schooling

The aim of the first stage of the statistical analysis is to obtain an estimate of the return to investing in an additional year of full time education in each of the LEAs in England and Wales. The wage equation that needs to be estimated in order to do this requires only a minor modification to the type of equation that is conventionally used when estimating the rate of return to education for individuals within a sample. There already exists a large volume of empirical literature attempting to estimate the return to schooling (β) in an earnings equation of the form:

$$\ln y_i = \alpha + \beta S_i + \delta X_i + \varepsilon_i \tag{3.5}$$

where S_i is the number of years of schooling
X_i is a vector of observable explanatory variables
δ is a vector of coefficients to be estimated
β is the rate of return to schooling
ε_i is a random error term

In equation (3.5), the coefficient β will only be an unbiased estimate of the rate of return to schooling if there is no correlation between the error term and any of the explanatory variables. There are several reasons, however, for believing that such an estimate of the return to schooling is biased. The most commonly referred to source of bias in the literature is due to the omission from the earnings equation of variables capturing ability. It is likely to be the case that individuals possess unobservable ability characteristics which influence both their level of schooling and their on-the-job productivity for any given amount of schooling.[11] As an example, consider a situation where there are two individuals who are similar in terms of their observable X variables in (3.5), but where one individual has higher unobservable ability. The more able individual may be observed as having invested in one extra year of schooling and receiving higher earnings than the less able worker. Part of the observed wage differential between the two workers will be due to the fact that the more able individual invested in an extra year of schooling, which is rewarded within the labour market. Another part of the differential will be due to the more able individual being associated with a higher productivity on-the-job for any given amount of schooling. In other words, even if the less able individual was observed with an extra year of schooling, they would still earn less than the more able individual. If this productivity enhancing effect associated with ability is not explicitly controlled for in the estimation of (3.5), all of the wage differential between the two workers would be attributed to the extra year of schooling. Under these circumstances, the estimate of the return to an additional year of schooling would be overstated. The coefficient β in (3.5) is interpreted as the increase in earnings associated with an extra year of schooling when all else is equal, but if unobservable ability rises with years of schooling, the coefficient may be biased upwards. More formally, the unobserved ability of individuals would be captured by the error tem in (3.5) and if this is positively correlated with both schooling and earnings controlling for schooling, the coefficient β would be biased upwards.

In the empirical literature, two main methods are used for estimating the rate of return to education when faced with the possibility of omitted ability bias. The first method involves including variables within an earnings equation like (3.5) that serve as proxies for an individual's level of unobserved ability. The most common type of variables included relate to scores obtained in ability tests undertaken at relatively young ages. Including such ability measures would be expected to reduce the upward bias in the estimated return to schooling since the coefficient β would be interpreted as the return to an additional year of schooling holding ability and all other variables constant. In a study using the NCDS, Dearden (1999b) finds that following the inclusion of variables relating to ability and family background into the wage equation, the estimate of the rate of return to education falls from 7.2% to 4.8%.[12] Using US data, Blackburn and Neumark (1995) also find that the OLS estimate of the return to schooling is biased upwards by around 40% when ability is not controlled for within the

[11] Most human capital models predict that those with higher ability devote more time to investment in human capital in each period.

[12] The omission of family background variables may introduce a similar source of bias to that of omitted ability if family background characteristics are correlated with both earnings and schooling.

wage equation. Existing evidence, therefore, does suggest that estimates of the rate of return to education are overstated when the effects of ability are not adequately controlled for.

A second method for reducing the bias arising from omitted ability is to examine the levels of schooling and wages for siblings or identical twins. The advantage of considering a sample of such individuals is that siblings will possess the same family background variables, while identical twins will also be associated with similar levels of ability. An earnings equation similar to that of (3.5) may be specified for each individual within the twin-pair, with the unobserved ability of each individual being captured by the error terms. By taking the difference between these two wage equations, the difference in earnings between the twins in family *f* would be related to the difference in their observable explanatory variables and an error term:

$$\Delta \ln y_f = \gamma + \beta \Delta S_f + \delta \Delta X_f + \mu_f \tag{3.6}$$

The differencing procedure eliminates the ability component from the error term in (3.6) if unobservable ability is assumed to be the equal for both twins. Under these circumstances, there is no correlation between the error term and the schooling variable arising from ability, removing the source of bias from the estimate of the return to schooling. In order to obtain an estimate of the return to schooling, however, it is necessary that the difference in schooling between the twins is non zero. Any differences that do exist in their years of education will not be related to family or ability variables since these are assumed to be the same for each twin, but instead may simply be due to exogenous factors or errors in measuring schooling. The results obtained from studies of twins generally find that the estimate of the return to schooling produced from an equation like (3.6) is lower than that of (3.5). Taubmann (1976) found that the return to schooling was 2.7% when a within twin-pair difference equation was estimated, whereas the estimate obtained from an equation like (3.5) for all individuals within the data was 7.9%. Recent evidence in the UK by Bonjour *et al* (2000) for a sample of female twins finds similar results with the estimated return falling from 7.7% when a conventional wage equation is estimated for all individuals to 3.9% for the difference equation.

It is often argued, however, that such studies of twins may understate the return to education if an adjustment is not made for the bias that arises as a result of errors in the measurement of years of schooling. Suppose in equation (3.5) that instead of having data on actual years of schooling (*S*), information was only available on reported schooling (S^*) which, due to measurement errors (*z*), differs from actual schooling (i.e $S_i^* = S_i + z_i$). When estimating an earnings equation like (3.5) that substitutes reported schooling in place of actual schooling, the errors associated with reported schooling, z, will now be encompassed in the error term of the earnings equation.[13] As a result, the error term in the wage equation will be correlated with the reported schooling variable and the estimated return to schooling will be biased downwards.[14] In order to obtain an unbiased estimate of the return to schooling, it is necessary to identify a suitable instrument that is highly correlated with actual schooling, but is uncorrelated with either the measurement error term or the wage equation error term. In the twins literature, Ashenfelter and Krueger (1994) proposed a method of correcting for measurement error which involved re-estimating (3.5) using instrumental variables where years of schooling is captured by the value given when each twin is asked to report on the amount of schooling undertaken by their sibling. This method will correct for the bias associated with measurement error if one twin's report of their sibling's education is correlated with their sibling's actual education, but is uncorrelated with either the measurement error (z) or the error in their sibling's original earnings equation (ε). Using this technique, Bonjour *et al*'s estimate of the return to schooling was found to rise from 3.9% to 7.7%, which is by coincidence the same as their initial OLS estimate.[15]

Instrumental variables are also used to correct for the bias in the estimated return to education arising from the potential endogeneity of years of schooling. It may be the case that the number of years an individual devotes to schooling is determined partly by the earnings that they expect to receive in the labour market. Individuals with the most to gain by entering the labour market may decide to invest less in full time education. A structural equation could then be written where years of schooling are related to earnings and a set of explanatory variables (Z). Along with the earnings equation of (3.5), these two equations would form a simultaneous equation system with earnings and schooling being jointly determined. The consequences of estimating (3.5) without recognising the endogeneity of years of schooling would be that the schooling variable in (3.5) would be correlated with the error term and the estimated rate of return would be biased. If a positive shock to the error term in (3.5) raises earnings and the feedback effect of this increase in earnings is to lower years of schooling, the direction of the bias would be downward. The technique commonly used to obtain unbiased coefficients is to re-estimate the wage equation by two stage least squares. In order to do this, it is necessary to identify at least one variable among the Z variables in the schooling equation

[13] Using $S_i = S_i^* - z_i$, the wage equation becomes $\ln y_i = \alpha + \delta X + \beta(S_i^* - z_i) + \varepsilon_i$, which may be rewritten as $\ln y_i = \alpha + \delta X + \beta S_i^* + \varphi_i$ where the wage equation error term becomes $\varphi_i = \varepsilon_i - \beta z_i$

[14] Gujarati (1995) p.469 discusses the case where explanatory variables are measured with error.

[15] In Ashenfelter and Krueger's study, the estimated rate of return rose from 9% to 17% when the twin pair difference equation was estimated by IV rather than OLS.

that is not contained within the X variables, or correlated with the error term in the earnings equation. There are a number of studies that exploit natural variations in the level of schooling to provide this necessary instrument for schooling. A recent example of this approach is by Harmon and Walker (1995) who take advantage of the fact that compulsory changes in the minimum school leaving age in the UK would have exerted exogenous changes in years of schooling among a sample of males from the Family Expenditure Survey. A structural equation for schooling is specified that is identified through two dummy variables indicating whether the individual faced a minimum school leaving age of 15, or 16.[16] In the reduced form equation, both of these dummy variables were found to exert positive and significant effects on the number of years of schooling. When the earnings equation was then estimated by 2SLS, the estimated return to schooling was found to be 15%, which was considerably higher than the 6% estimate obtained when the equation was estimated by OLS and thus ignoring the potential endogeneity of schooling.

The estimate of the return to schooling produced from an earnings equation of the form (3.5) may therefore be biased for a variety of reasons. The omission of ability and family background effects are often argued to result in the estimated return being overstated, while measurement error and the potential endogenity of schooling create a downward bias in the estimated return. Evidence from existing empirical studies generally supports the idea that estimates of the return to schooling are indeed biased in this way. It is often argued that initial estimates of the return to schooling obtained by OLS may actually turn out to be a reasonable estimate since there is a tendency for the upward bias associated with omitted ability to be offset by the downward bias arising from measurement error and endogeneity. Using NCDS data, Dearden (1999a) finds that the effects of these various forms of bias tend to cancel each other out, although most other studies find that even after controlling for omitted ability, measurement error and endogenity, the estimated return is still less than conventional OLS estimates.[17]

3.3.2 Stage 1: Estimating the return to schooling for each LEA in England and Wales

Section 3.1 discussed some of the general issues that need to be considered when attempting to estimate the return to schooling from a simple earnings equation. The studies referred to previously were concerned with obtaining an estimate of the average return for all individuals within the relevant sample. For the purposes of the present study looking at the effects of

[16] The dummy variable capturing a leaving age of 14 represents the excluded case. The minimum school leaving age was raised to 15 in 1947, and then to 16 in 1973.
[17] See Blackburn and Neumark (1995), and Dearden (1999b) who finds an initial estimated return of 7.2%, which falls to 4.8% after controlling for ability, and which then rises to 5.5% using IV and controlling for ability.

quality, the first stage of the methodology involves obtaining an estimate of the average return for individuals who were educated within each of the 148 LEAs identified within England and Wales. It is possible that a year of education in some LEAs is rewarded more highly in the labour market than in others. The overall aim of this study, which is then pursued in the second stage, is to analyse whether the quality of education plays a role in determining these estimated LEA-specific rates of return to schooling.

In order to determine the return to education for each LEA, equation (3.7) is estimated, which is a modified version of (3.5) in the sense that it includes interactions between individual *i*'s level of schooling (S_i) and dummy variables indicating in which of the 148 LEAs the individual was educated in. For each individual, therefore, only one of the 148 terms in brackets will take a positive value, and will equal their years of schooling. Estimation of equation (3.7) for all individuals in the sample would then yield 148 estimates of the return to education, one for each LEA.

$$\ln y_i = \alpha_0 + \alpha_1 REGION_i + \delta X_i + \beta_1 (S_i * LEA1_i) + ... + \beta_{148} (S_i * LEA148_i) + \varepsilon_i \qquad (3.7)$$

In this equation, *REGION* represents a set of 11 dummy variables indicating the standard region of the country in which the individual resides in at age 33. *X* captures the set of conventional explanatory variables and δ is a vector of coefficients to be estimated. Using a similar notation to that of Card and Krueger, equation (3.7) could also be written in the following form for individual *i*, educated in LEA *l*, and currently residing in one of the eleven regions *r*:

$$\ln y_{ilr} = \alpha_0 + \alpha_r + \delta X_{ilr} + \beta_l S_{ilr} + \varepsilon_{ilr} \qquad (\alpha_r \text{ is a regional fixed effect})$$

The equation given by (3.7) suggests a first stage regression that is essentially a simplified version of Card and Krueger's first equation expressed in (3.3). In Card and Krueger's approach, the return to education consists of two separate components- a state of birth specific component, and a region of residence specific component. Two individuals who were educated in the same state and invested in an identical amount of schooling, but who currently reside in different regions, may have different earnings because a year of education is rewarded more highly in some regions than others. Similarly, the earnings of two individuals living in the same region and with the same amount of schooling, but who were educated in different states, may not be equal as an extra year of schooling undertaken in some states is rewarded more highly than in others. As was mentioned in section 2.3, being able to identify these two specific components requires observing individuals who are mobile, i.e. who were educated in one state, but reside in a different region.

The first stage equation given by (3.7) is primarily different to that of Card and Krueger's in that it does not identify a specific component of the return to education that is attributable to the regional labour market that the individual is currently employed in. Instead, any effect that the current region of residence has on earnings is modelled as operating solely through the intercept term.[18] Within this set-up, two individuals educated in the same LEA and with the same amount of schooling, but currently living in different regions may have different earnings as a result of regional effects shifting the entire earnings-schooling relationship. As in Card and Krueger's approach, however, equation (3.7) does allow the rate of return to education to vary across each of the LEAs in England and Wales. An extra year of education received in one LEA may be rewarded more highly in the labour market than an extra year undertaken in a different LEA. In this case, a wage differential may exist between two workers currently employed within the same regional labour market and with the same quantity of schooling because of differing rates of return to their education.

Following the discussion presented in section 3.1, there are reasons for believing that the estimates of the LEA-specific returns to education obtained from equation (3.7) may be biased. The omission of variables capturing ability may lead to upwardly biased estimates being obtained, while the possibility that schooling is measured with error, or is endogenously determined, may generate coefficient estimates that are biased downwards. The implications of obtaining biased LEA-specific rates of return from (3.7) are potentially serious since these estimates are carried over into the second stage of the statistical analysis. In recognition of the findings of the existing literature on estimating the returns to schooling, an earnings equation similar to that of (3.5) is initially estimated where a single estimate of the return to schooling is obtained, reflecting the average return among all of the individuals within the sample. The purpose of doing this is to explore the extent to which the various sources of bias influence the return to education and to therefore gain an insight into how equation (3.7) should be estimated in order to obtain reliable estimates of the LEA-specific returns used in the second stage. The earnings equation including a single estimate of the return to schooling is initially estimated by OLS and then re-estimated with the inclusion of variables capturing ability in order to determine the extent to which the omission of ability generates an upward bias in the return to schooling. Following this, the equation is then estimated by two stage least squares with and without the ability controls to see whether the possible existence of measurement

[18] Card and Krueger also include intercept effects in (3.3) for region of residence and state of birth.

error and endogeneity lead to the estimated return being understated. The results from undertaking these estimations are reported in detail in section 5.1, but it is found that after attempting to correct for the various sources of bias, the 11.8% estimate of the return to schooling is similar to the initial OLS estimate of 10.5%. Since it would appear that within the sample of NCDS males, the various sources of bias approximately offset each other, the estimates of the LEA-specific returns required for the second stage of the analysis are obtained by estimating equation (3.7) by OLS.

3.3.3 Stage 2: The effects of quality on the LEA-specific rates of return to schooling

Having obtained OLS estimates of the return to schooling for each of the LEAs in England and Wales, the second stage of the statistical analysis involves examining whether the quality of education is an important factor in determining an LEA's rate of return. In order to do this, a similar equation to that defined by Card and Krueger is estimated where the 148 LEA-specific returns (β_l) obtained from the first stage are regressed on measures of school quality within the LEA.

$$\beta_l = \theta + \gamma_1 Q_l + \gamma_2 TYPE_l + \gamma_3 NBHOOD_l + \gamma_4 FAMILY_l + \gamma_5 AREA_l + \mu_l \qquad (3.8)$$

In this equation, Q contains a set of variables capturing the average level of quality among the secondary schools within each LEA, while γ_l is the relevant vector of quality effects to be estimated. The measures of quality included are mean pupil-teacher ratio, expenditure per student and teacher salary. It would be expected that the coefficient associated with the pupil-teacher ratio is negative, while the other two quality measures are anticipated to positively affect the return to schooling. Further variables relating to the type of schools contained within an LEA are included in the term *TYPE*. It may be the case that after controlling for quality, single sex schools are associated with a higher return to education than mixed schools. An LEA that places 100% of pupils into single sex schools may then be observed as having a higher rate of return than another LEA that is identical with respect to the standard measures of quality, but that only operates mixed schools. Including a measure of the percentage of pupils in an LEA that attend single sex schools may then capture the extent to which the segregation of students according to gender influences the performance of all pupils within an LEA, holding quality constant. The other variable included within *TYPE* is the proportion of pupils within an LEA who attended a grammar school. This variable is designed to capture the extent to which segregating pupils according to their ability is beneficial to all students within an LEA. It is often argued that educating individuals in groups with similar ability generates peer effects, raising the performance of both low ability and high ability pupils. The proportion of individuals attending grammar schools may then be interpreted as the extent to which an LEA segregates pupils according to their ability and the corresponding effect that this selection process has on all pupils within an LEA.[19]

Equation (3.8) also includes a set of variables *NBHOOD* designed to capture any local environment factors that may influence the return to education. As discussed by Dolton and Vignoles (1996) and Dearden *et al* (1998), local authorities with a greater level of deprivation among its population tend to receive higher levels of funding. Under these circumstances, a relatively deprived LEA may be observed with higher expenditure per pupil, but as a consequence of pupils living in deprivation, be associated with a lower rate of return to education. Part of the additional funding received by deprived LEAs may be used to provide free school meals, meaning that not all of the extra expenditure per pupil can be linked to the quality of education received. For this reason, the percentage of pupils within an LEA receiving free school meals is included as a measure of deprivation. By including this variable in (3.8), it is possible to estimate the effect that higher expenditure per pupil has on the return to education after allowing for any expenditure differentials that exist between LEAs as a result of differing levels of deprivation.

A potential problem with estimating equation (3.8) is that the coefficients associated with the quality variables may be biased if variables that are correlated with both the return to education and the level of quality are omitted. An example of such a variable is family income, which may raise a pupil's rate of return to education and also influence quality if high income parents select schools with, for example, a lower pupil-teacher ratio. Family effects of this nature would then be expected to lead to the coefficients attached to the quality variables being overstated. The extent of this bias, however, is generally believed to be particularly strong when quality is measured at the school level. This is because high income parents are likely to select the highest quality school within the LEA in which they currently live. If parents are able to choose the best schools in their existing LEA, it is less likely that high income parents will locate themselves in a different LEA where the average quality of schools is higher. Under these circumstances, average family income within an LEA may not be highly correlated with the average quality of education in the same LEA. The potential bias

[19] Dearden *et al* (1998) argue that attending a grammar school is a signal of higher ability and so should be included in the individual's earnings equation in order to obtain unbiased estimates for the coefficients associated with the quality variables. When regressing LEA-specific returns on control variables measured at the LEA level as in (3.8), however, the interpretation of grammar school attendance differs. LEAs with a higher proportion of pupils attending grammar schools does not necessarily reflect a higher level of mean ability within the LEA. If the distribution of ability across LEAs is similar, the proportion attending grammar schools will represent the proportion of the individuals in the upper part of the ability distribution who are educated separately.

associated with omitting family background variables, therefore, may not be too serious when estimating an equation like (3.8) where quality is measured at the LEA level rather than at the school level. Despite this, some additional variables capturing family effects measured at the LEA level (*FAMILY*) are included within the second stage. These variables relate to the mean monthly income of parents within an LEA and the mean educational attainment of parents.

Any additional factors affecting rates of return arising from geographic location are captured by the term *AREA*, which is a set of ten regional dummy variables indicating the region of the country in which the LEA is located.[20] Card and Krueger control for such factors in the second stage by regressing their estimated state of birth specific returns on a set of dummy variables covering each possible state of birth. They are able to include state of birth dummy variables since for each state of birth, there are three estimated returns- one for each of the three cohorts. For equation (3.8), however, the LEA-specific returns obtained from the first stage could not be regressed on LEA dummies since only one estimate is obtained for each LEA. For this reason, it is necessary to use a more aggregated regional classification when attempting to capture any additional local environment factors that affect the returns to education.

3.4 Description of the data

In order to undertake the two stage statistical approach outlined in section 3, two main data sources are used. The National Child Development Study (NCDS) contains detailed information on individuals' educational attainment, labour market experience, and earnings at certain stages of their lives. This data set is used to estimate the first stage earnings equation expressed in equation (3.7). Once the estimated LEA-specific returns to education have been obtained, information relating to the average quality of education within each LEA is required for the estimation of the second stage equation given by (3.8). The NCDS itself contains some information relating to the quality of schooling received by each individual, which may be averaged for all those educated in each of the LEAs. In addition, data obtained from The Chartered Institute of Public Finance and Accountancy (CIPFA) provides a range of educational statistics for each of the LEAs in England and Wales. The purpose of this section is to provide a detailed description of the way that these data sets are used for estimating the two relevant equations.

[20] There are only 10 regions in which the LEAs may be located since only those in England and Wales are considered. The eleventh region of current residence identified in the earnings equation relates to Scotland.

3.4.1 Estimating the LEA-specific returns to schooling

The primary source of data used in this study is the National Child Development Study, which is a longitudinal survey of individuals born in the UK during the first week of March 1958. Thus far, there have been five follow up surveys that were undertaken when the cohort members were aged 7, 11, 16, 23, and 33 years. In preparing the data necessary for the estimation of the earnings equation, information for each individual was extracted from the four most recent sweeps of the NCDS. The fifth sweep, taken when the cohort members were aged 33, was used to provide some of the key variables within the earnings equation, such as labour market experience, characteristics of the current employer, and earnings. The dependent variable used in equation (3.7) relates to usual gross weekly income received in the current job. Only individuals who were full time employees at age 33 are included within the final sample. Information contained within the fifth sweep of the NCDS was also referred to when forming the set of explanatory variables, X, which appear in the earnings equation. Contained within X are sets of dummy variables indicating the number of employees at the current place of work (*SIZE*), marital status (*MARRIED*), and union membership (*UNION*). The number of hours worked in the current job (*HOURS*) and years of labour market experience (*EXP*) are the final variables included in X.[21] Dummy variables are also included in equation (3.7) to indicate which of the 11 standard regions the individual resided in at age 33 (*REGION*).[22]

The other two important variables on the right-hand-side of the earnings equation relate to the number of years of schooling and the LEA in which the cohort member received their schooling. Several different variables were constructed in attempting to measure the number of years of education accumulated by each individual, S_i. The main method used for measuring years of schooling is to refer to the date at which the individual entered the labour market for the first time. In terms of the life cycle human capital model, individuals enter the labour market at the point where the fraction of their time devoted to human capital investment falls marginally below one. With an optimal investment ratio below one, individuals divide their time between working and accumulating additional human capital. The part of the life cycle, however, where the optimal investment ratio equals one, and so where individuals devote all of their available time to human capital accumulation, corresponds to the period of full time schooling. The date at which an individual enters the

[21] Actual labour market experience is calculated by summing the total duration of the time spent in jobs up to the age of 33 years.

[22] In the fifth sweep of the NCDS, there is a relatively high number of missing observations relating to standard region at age 33. In order to maximise the sample size when estimating (3.7), individuals with no regional data available at age 33 were assigned the standard region that they reported in sweep four if they did not change address between sweeps four and five.

labour market for the first time may therefore be viewed as an approximation for the number of years devoted to full time education. This measure of years of schooling was calculated from the fourth sweep of the NCDS using the variables relating to the month and year in which the individual started their first job.

Using the date of labour market entry to measure years of schooling is unconventional and not consistent with the way that this variable is measured in the studies discussed in sections 2 and 3. Generally, variables relating to years of schooling are derived from the level of qualifications that an individual holds at a given point in time, or from a diary containing the individual's main activity in each month (Dearden 1999b). There are a few potential problems with using entry date as a measure of schooling in the equation for earnings at age 33. The most obvious problem is that an individual may experience a period of unemployment between leaving school and starting their first job. In this case, the date of labour market entry will overstate the number of years spent in full time education. A second problem would arise if, after entering the labour market, workers gain additional qualifications in the years leading up to age 33. These extra qualifications would be expected to positively affect earnings at age 33, but would not be explicitly captured by the measure of schooling. The omission of variables relating to qualifications obtained after labour market entry may then introduce an additional source of bias associated with the estimated return to schooling. As a result of these concerns, a second method is used for incorporating educational attainment into the wage equation. In this method, the number of years of schooling, S_i, was calculated by adding up the number of months that an individual was in full time education between ages 16 and 23. Information concerning such activity in each month is given in sweep four of the NCDS. The fifth sweep of the NCDS was then used to construct a set of dummy variables indicating the highest qualification obtained by each individual between NCDS4 and NCDS5. This set of educational dummy variables and the alternative measure of years of schooling may then be included in the wage equation.

Another way of including educational attainment in the earnings equation would be to use NCDS5 to calculate the total number of years spent in education up to age 33. The method described above, however, where years of education up to age 23 are identified separately may be more appropriate for the purposes of this study. This is because when obtaining the LEA-specific returns to education in (3.7), each individual's quantity of education is attached to a dummy variable indicating the LEA in which their secondary education was undertaken. Within this framework, all additional years of education accumulated by the individual beyond the start of secondary school continue to be associated with the same LEA. The implications of this are that a year of education undertaken at an age such as 30 would be taken into account when estimating the return to education for a given LEA. It seems unlikely, however, that the return to a year of education undertaken at a later age is determined by the LEA in which the individual attended secondary school. The LEA is most likely to affect the rate of return to the years spent in school, although it could influence the value of subsequent education if attending a school within a high quality LEA raises the probability of receiving higher quality further education. It may not be unreasonable, therefore, to assume that the return to years of education accumulated up to the age of 23 is dependent on the initial LEA. Any education undertaken beyond this age could be included separately within the earnings equation through dummy variables with the added assumption that the returns to such education are homogeneous.

The idea that the LEA mainly determines the value of early educational attainment is also a strong reason for using the date of labour market entry as a way of capturing years of full time education in the earnings equation of (3.7). The value of human capital built up by an individual between the start of secondary school and the time that they first enter the labour market may be dependent on the quality of the schools within the LEA by which they are covered. The return on any human capital investments undertaken beyond the point of entry, however, may be determined by factors other than the LEA. Using the measure of schooling derived from entry dates may therefore provide a convenient way of identifying the part of the cohort member's education that is associated with heterogeneous returns arising from their LEA. This schooling variable is the preferred measure of education in the empirical analysis that follows, although all of the estimations are repeated using the alternative method of including years of schooling up to age 23 and a set of dummy variables indicating further qualifications between ages 23 and 33.

3.4.2 The measures of school quality used within the second stage regression

For the estimation of the second part of the statistical analysis, it was necessary to obtain a set of variables, Q, capturing the quality of education associated with each of the LEAs. Some of these LEA-specific quality measures were derived from the NCDS, while others were obtained from educational statistics produced by CIPFA in 1970. In order to calculate the quality measures derived from the NCDS, it was first necessary to identify the LEA in which each of the 18,000 cohort members received their education at age 11. This age corresponds to the time at which the cohort were on the verge of starting their secondary education. Due to the existence of a different education system in Scotland, only LEAs located within England and Wales are considered within the study. In total, the NCDS identifies 152 LEAs within England and Wales, which was then reduced to 148 following the exclusion of the Isle of Man, Isles of Scilly, Guernsey, and Jersey. These four LEAs were excluded from the analysis since data relating to school quality was unavailable from CIPFA for these areas. Overall, it was possible to observe 12,652 members of the NCDS cohort who were educated in the 148 LEAs in England and Wales.

For these 12,652 individuals, information was obtained from the NCDS sweep taken at age 16 relating to the characteristics of the secondary school that each individual attended. At this age, the NCDS cohort would have been in the final year of their compulsory schooling. In particular, it was possible to calculate the pupil-teacher ratio that existed within each individual's school. It could also be determined whether the school attended was either mixed or single sex. Additionally, it was possible to observe whether the individual's school was a comprehensive, grammar, or secondary modern school. The measures of quality given in the NCDS may therefore be seen as being school-specific since information on these variables is recorded for each cohort member. When estimating equation (3.8), however, it is necessary to obtain measures of quality relating to each of the LEAs, which may then be included within Q. Since it is known in which LEA the 12,652 individuals were educated in, it was possible to obtain these LEA-specific quality measures by calculating the mean value of the NCDS quality measures for all of the individuals educated in each of the 148 LEAs. For example, the variable denoted by *NCDSPTR16*, captures the mean pupil-teacher ratio observed among all of the individuals educated within a given LEA.

For the 148 LEAs identified from the NCDS, it was also possible to obtain some additional statistics relating to the mean characteristics of the secondary schools located within each LEA from the Education Statistics produced by CIPFA. In addition to another measure of the pupil-teacher ratio (*CIPFAPTR*), data was also available on average teacher salary (*CIPFASAL*) and total expenditure per pupil (*CIPFAEXP*). These measures of quality are commonly used in the existing studies examining the effects of school quality that were discussed in section 2. The figures for these CIPFA quality variables, were then matched to each of the LEAs identified within the NCDS. The quality measures obtained from CIPFA relate to the year 1970, which corresponds to the time in which the cohort would have been approaching the end of their first year of secondary education. The set of variables represented by Q in (3.8), therefore, includes NCDS measures of LEA quality relating to the time when the cohort was nearing the end of their secondary education, and CIPFA quality measures covering the time when the cohort had just started secondary schooling.[23] Table 3.1

[23] The CIPFA quality measures are also available for the year 1974, which is when the NCDS measures are calculated, but information is missing for certain LEAs as the classification of LEAs changed close to this time.

below shows the means and standard deviations for the LEA-specific measures of quality obtained from the NCDS and CIPFA.

Control Group	Variable Name	Mean	Standard Deviation	Minimum	Maximum
Q	*NCDSPTR16*	17.81	1.46	8.68	22.95
	CIPFAPTR	18.08	1.03	13.5	20.3
	CIPFASAL (£)	101.69	7.68	83.21	133.81
	CIPFAEXP (£)	170.37	13.73	133.72	218.67
TYPE	*NCDSMIXED*	0.75	0.21	0.17	1
	NCDSBOYS	0.12	0.12	0	0.50
	NCDSGIRLS	0.12	0.12	0	0.63
	NCDSCOMP *	0.61	0.35	0	1
	NCDSSEC *	0.26	0.26	0	1
	NCDSGRAM *	0.12	0.13	0	0.67
NBHOOD	*NCDSMEALS*	0.11	0.07	0	0.46
	CIPFAPOP (popln/acre)	8.77	7.79	0.06	40.08
FAMILY	*NCDSFAMINC* (£) **	305.64	37.86	152.67	428.46
	NCDSFEDUC	3.88	0.45	3	5.33
	NCDSMEDUC	3.92	0.41	3	5.67

Table 3.1 Summary statistics for the 148 LEA-specific quality measures

Notes *Q* variables capture pupil-teacher ratios at 16 and 11, teacher salary, and expenditure per pupil
TYPE variables give the proportion of individuals within an LEA attending mixed, boys, girls, comprehensive, secondary modern, and grammar schools respectively
NBHOOD variables relate to the proportion of individuals at 11 receiving free school meals in an LEA, and population density within the LEA
FAMILY variables include mean family income, and mean educational attainment of fathers and mothers within an LEA (captured by an index ranging from 1 to 10)

* denotes mean calculated from 147 LEAs as no data was available for LEA 85
** denotes mean calculated from 147 LEAs as no data was available for LEA 116
A full description of the variables is given in appendix B

In addition to the measures of school quality (*Q*), table 3.1 also provides some summary statistics for the other groups of variables included in the second stage equation, (3.8). The variables relating to the type of schools found within each LEA are derived from the NCDS using a similar technique to that which was used when calculating the NCDS measure of the pupil-teacher ratio at age 16, *NCDSPTR16*. Using the sample of 12,652 individuals for whom data was available concerning their LEA at age 11, it was possible to derive a set of dummy variables indicating whether the individual went to an all boys school, an all girls school, or a mixed school. By taking the mean value of these dummies for all of the individuals educated within a particular LEA, it was possible to determine the proportion of individuals in that LEA who attended each type of school. The variable *NCDSMIXED*, therefore, gives the proportion of pupils within an LEA who attended a mixed school, whereas the variables *NCDSBOYS* and *NCDSGIRLS* capture the proportion of pupils educated in all boys and all girls schools respectively. The average values of these variables taken across all of the LEAs are presented in table 3.1 where it may be seen that on average, 75% of pupils in an LEA attended a mixed school and 25% attended a single sex school. An identical procedure was then followed to determine the proportion of individuals within each LEA who attended either a comprehensive, secondary modern, or grammar school. The average of the variables *NCDSCOMP*, *NCDSSEC* and *NCDSGRAM* across all of the LEAs suggests that on average, 61% of students attended a comprehensive school, 26% a secondary modern school, and 12% a grammar school.

The third set of variables that were derived in order to estimate equation (3.8) relate to local environment factors within each of the LEAs. In particular, the proportion of pupils who received free school meals at age 11 is included as a measure of social deprivation. Like the school type variables described above, this variable is derived from the NCDS by constructing a dummy variable indicating whether each individual received free school meals and then taking the average for all of the individuals within each of the LEAs. As may be seen in table 3.1, the percentage of pupils receiving free school meals ranged from 0% to 46%, with the average being 11%. The other variable included within the group of local neighbourhood characteristics is the population density within each LEA in 1970, *CIPFAPOP*. This variable is obtained from the CIPFA Education Statistics and is measured as the total LEA population per acre.

The final group of variables summarised in table 3.1 relate to the mean family characteristics of pupils within each LEA. These variables are again derived from the sample of 12,652 individuals extracted from the NCDS. For each individual it was possible to calculate the net monthly income received by their parents, which could then be averaged across all the individuals educated within a particular LEA, giving the variable *NCDSFAMINC*. In addition, the variables *NCDSMEDUC* and *NCDSFEDUC* measure the mean education attainment of the pupils' mothers and fathers in each local authority. These two variables are constructed from an index with the value one representing the lowest educational attainment and the value 10 representing the highest attainment. Further details concerning the derivation of the family characteristics variables are given in appendix B.

The variables used within the second stage of the statistical analysis are therefore obtained from two sources. Data from the Education Statistics produced by CIPFA is used to provide the LEA-specific measures of quality that have been used in previous UK studies relating to teacher-pupil ratio, expenditure per student, and average teacher salary. Additional control variables measured at the LEA level are difficult to obtain, partly because the definition of LEAs in England and Wales has changed several times over the last thirty years. For this reason, the sample of 12,652 individuals in the NCDS cohort was constructed in order to derive the necessary control variables measured as LEA averages. A potential problem with deriving these LEA control variables from the NCDS is that some of the 12,652 individuals who reported being educated in one of the LEAs in England and Wales at age 11 may have switched to a different LEA at age 16. Inspection of the data revealed that approximately 11% of the 12,652 individuals were covered by a different LEA by the time that they were 16.[24] As a result of this, all of the LEA control variables derived from the NCDS were re-calculated using the sample of 11,288 individuals who were not observed as switching LEAs between ages 11 and 16 years. Doing this appeared to make little difference to the mean values of the LEA variables reported in table 3.1. For example, mean family income was calculated to be £306.54 and the mean percentage of students attending comprehensive schools across the LEAs was found to be 61%. When re-calculating these LEA variables for the smaller sample containing those who did not switch LEAs, however, it was not possible to derive values for all of the LEAs covered in table 3.1.[25] In order to maximise the number of observations in the second stage regression, the set of control variables that were derived from the initial 12,652 individuals are therefore used in the statistical analysis. Given that this set of variables appear similar to those based on the sample who did not switch LEAs, it would see reasonable to use these in the second stage and reduce the number of observations dropped as a result of missing LEA control variables.

3.5 Results

For the sample of 12,652 males and females known to have been educated in one of the 148 LEAs in England and Wales, data for the additional variables required to estimate the first stage earnings equation was merged in for each individual. By 1991, when the NCDS cohort was aged 33 years, earnings data was only available for 2866 full time male employees at that time. No earnings data was observed for any individuals educated in four of the local authorities, meaning that only 144 LEAs were now represented within the sample.[26]

[24] Although the definition of LEAs altered in 1974, the NCDS retains the same coding for the waves taken at ages 11 and 16 years.

[25] In addition to the missing data for LEA numbers 85 and 116 in table 3.1, no data for some variables was available in the sample of 11,288 for LEA numbers 5, 51 and 121.

[26] LEA numbers 85,92,107 and 116 were no longer represented.

Incorporating the data for the date of labour market entry reduced the sample size to 2413, with 143 LEAs being represented.[27] Missing observations on the amount of experience accumulated by age 33 further reduced the size of the sample to 2307 workers. It was then only possible to derive the standard region of residence at age 33 for 1576 males. As a consequence of missing regional data, individuals from a further five LEAs were excluded from the sample.[28] For the sets of dummy variables relating to establishment size, marital status and union membership, separate categories were identified for those with missing values rather than eliminating them from the final sample. Overall, therefore, the final sample of individuals extracted from the NCDS consisted of 1576 men who received their secondary education in 138 of the LEAs in England and Wales.

This sample of males obtained from the NCDS was then used to estimate the equations outlined in section 3. The first equation estimated in section 5.1 is a conventional earnings equation of the form expressed in (3.5). This equation produces an estimate of the return to education for the NCDS sample as a whole rather than identifying LEA-specific returns. Several versions of this equation are estimated in order to determine the extent to which the estimated rate of return alters when an attempt is made to correct for the various sources of bias discussed in section 3. The results from performing these regressions suggest that the OLS estimate of the return to education may, afterall be a reasonable approximation. Sections 5.2 and 5.3 then present the results obtained from estimating the two separate stages of the statistical analysis, given by equations (3.7) and (3.8).

3.5.1 The returns to education for the NCDS sample

The aim of the first stage of the statistical analysis is to obtain estimates of the return to education in each of the LEAs in England and Wales by estimating equation (3.7). This equation, however, represents a modified version of the type of equation used within most studies for deriving a single estimate of the return to schooling. It is worthwhile at this point estimating an equation of the form given in (3.5) for the sample of 1576 males taken from the NCDS. The first column of table 3.2 below shows the OLS results obtained from estimating an equation that relates the log of weekly earnings to years of schooling (S), which is captured by the age at which the individual first entered the labour market. In addition, weekly hours, experience, experience-squared, establishment size, marital status, union status, and standard region at age 33 are included as explanatory variables. It may be seen from column 1 that the

[27] Due to missing data on the date of entry, no individuals educated in LEA 126 remained.
[28] The five LEAs lost are numbers 13,18,43,110 and 121. Missing observations for standard region at age 33 were recoded to equal the standard region at age 23 if the individual did not report changing address between 1981 and 1991. Doing this prevents LEA128 being unrepresented in the final sample.

return to an additional year of schooling is found to be 10.5%, which is higher than the initial estimate of 7.2% obtained by Dearden (1999b) who also uses the NCDS.

Variable	**1 (OLS)**	**2 (OLS)**	**3 (IV)**	**4 (IV)**
S (ENTRY AGE)	0.105 (10.570)	0.081 (7.977)	0.186 (6.606)	0.118 (3.460)
HOURS	0.010 (7.118)	0.010 (7.265)	0.108 (7.217)	0.011 (7.311)
EXP	0.060 (2.041)	0.040 (1.370)	-0.009 (0.233)	0.013 (0.358)
EXPSQ	-0.001 (1.171)	-0.001 (0.526)	0.003 (1.469)	-0.001 (0.535)
Ability controls	No	Yes	No	Yes
R-squared	0.2205	0.2602	0.1861	0.2535
F	18.99	16.87	15.43	15.12
N	1568	1568	1568	1568

Table 3.2 Estimation of (3.7) without LEA-specific returns; dependent variable is log gross weekly pay

Notes Other variables included are establishment size, marital status, union membership, and regional dummies; all regressions include a constant term
S is schooling measured by the age in years at which the individual's first job started
t-statistics are shown in brackets
The sample size *N* is lower than the 1576 mentioned in the text due to missing observations on the set of dummy variables capturing ability at age 11.

As may be recalled from the discussion in section 3, OLS estimates of the return to schooling may be overstated if ability is not explicitly controlled for in the earnings equation. The equation was therefore re-estimated with the inclusion of a set of ten dummy variables indicating each individual's score on tests taken at age 11. The results from performing this regression are presented in column 2 of table 3.2. In performing an *F* test of this regression including the ability controls against the restricted model suggested by column 1, the measures of ability were found to be significant.[29] It may be seen that after controlling for ability, the return to schooling falls to 8.1% suggesting that the omission of ability in column 1 generates an upward bias in the OLS estimate of the rate of return. Even after controlling for ability, however, the coefficient associated with *S* may remain biased, this time in a downwards direction, due to the possibility of measurement error or endogeneity. The earnings equation was therefore re-estimated by two stage least squares, producing the results given in column 4 of table 3.2. In undertaking this regression technique, identification of the structural equation for years of schooling was achieved through a set of family background variables.[30] The estimated return to education in the wage equation was then found to be 11.8%, which is slightly higher than the initial OLS estimate of 10.5%.

[29] The *F* statistic was calculated to be 9.15, where the critical value at 1% is 3.07.
[30] These include father's social class at age 11, age mother and father left full time education, and interest shown in child's education.

The estimated returns to education reported in table 3.2 would therefore appear to be broadly consistent to those found in previous studies. The largest estimate of 18.6%, obtained by 2SLS estimation of the wage equation with no ability controls (table 3.2, column 3), is comparable to Harmon and Walker's (1995) UK estimate of 15% using a different data set. After correcting for biases arising from omitted ability, measurement error and endogeneity, the 11.8% estimate is higher than those reported in the study of female twins by Bonjour *et al* (2000), and by Dearden (1999b) using the NCDS. Although the estimated returns shown in table 3.2 are comparable with other studies, the measure of schooling used differs. In table 3.2, the schooling variable is based on the age at which the individual first enters the labour market rather than being obtained from educational attainment or the reported number of years spent in education. As an additional way of checking whether the estimated returns to schooling were consistent with the findings of other studies, the four equations in table 3.2 were re-estimated using an alternative measure of schooling. The total number of years spent in full time education by the age of 23, along with dummy variables indicating additional educational attainment between ages 23 and 33, were included in the wage equation in place of entry age. Using this method, the coefficient on years of education by age 23 was found to be 0.108, 0.084, 0.168, and 0.111 for the four regressions. These figures are therefore similar to those reported in columns 1 to 4 of table 3.2 suggesting that the use of labour market entry dates may be a suitable method for measuring schooling.

3.5.2 Estimates of the LEA-specific returns to schooling

Having established that the estimated return to education for the NCDS sample is comparable with those of other studies, the first stage of the statistical analysis was undertaken by estimating equation (3.7). This equation produces an estimate of the return to schooling for individuals who were educated in each of the LEAs in England and Wales. Although the NCDS identifies 148 local authorities, due to no earnings or entry age data being available for the representatives of five authorities, it is only possible to derive an estimate of the return to schooling for 143 out of the 148 LEAs. The total number of LEAs is reduced even further to 138 in the final estimation due to no information being available relating to the region of residence at age 33 for any males educated in five of the LEAs. Appendix B provides a full listing of the 148 LEAs and highlights the ones that are excluded from the analysis as a result of incomplete data. Tables 3.3a and 3.3b below present some of the results obtained from the estimation of (3.7) where years of schooling (S) is measured as the age at which the individual started their first job. The equation is estimated for a sample of 1576 males by OLS without the inclusion of the ability measures referred to in table 3.2.[31] Table 3.3a reports the coefficients and *t*-ratios associated with the control variables, while table 3.3b presents some summary statistics relating to the 138 LEA-specific estimated returns to education.

Variable	***Coefficient and t-ratio***
HOURS	0.010 (6.271)
EXP	0.067 (2.460)
EXPSQ	-0.002 (1.535)
SIZE2 (11-25)	0.147 (2.340)
SIZE3 (26-99)	0.141 (2.733)
SIZE4 (100-499)	0.287 (5.350)
SIZE5 (500+)	0.273 (5.065)
MARRIED	0.133 (4.552)
UNION	-0.074 (2.721)
REGION2 (N.West)	0.014 (0.124)
REGION3 (Yorkshire)	0.068 (0.768)
REGION4 (W.Midlands)	-0.067 (0.551)
REGION5 (E.Midlands)	0.023 (0.250)
REGION6 (E.Anglia)	-0.009 (0.087)
REGION7 (S.West)	0.191 (2.057)
REGION8 (S.East)	0.334 (3.851)
REGION9 (London)	0.326 (3.402)
REGION10 (Wales)	0.060 (0.238)
REGION11 (Scotland)	0.117 (0.735)
LEA-specific returns included	see table 3.3b
R-squared	0.2971
F	17.90
N	1576

Table 3.3a OLS estimation of equation (3.7) for males

Notes Dependent variable is log weekly gross pay at age 33 (1991)
t-ratios are shown in brackets and are calculated from robust standard errors
Excluded cases are- living in the north (*REGION1*) and those in firms with 1-10 employees (*SIZE1*)
Dummies are also included for missing observations on firm size, marital status and union membership

[31] The equation generating the LEA-specific returns to schooling was also estimated with the inclusion of the ability controls. The motivation for doing this and the results obtained are discussed in section 5.4 of this chapter.

The results shown in table 3.3a suggest that most of the variables included within the set of explanatory variables, *X*, have the expected influence on earnings. The more hours worked per week (*HOURS*) and the higher the number of employees at the current place of work (*SIZE2-5*) significantly increase earnings at age 33. Each additional year of actual labour market experience (*EXP*) also exerts a significantly positive effect on earnings, but at a diminishing rate. This is consistent with the findings of many studies that observe the existence of an earnings-experience profile that is concave. Being married (*MARRIED*) is found to significantly raise earnings, although being a member of a union (*UNION*) is observed as having a negative effect. Most of the coefficients associated with the regional dummy variables are found to be insignificant, although those living in the South West, the South East, or London have significantly higher earnings than those living in the default category of the North.

Number of positive estimated rates of return		137
Number of negative estimated rates of return		1 (LEA57, Northamptonshire)
Mean rate of return		0.100
Highest positive return		0.185 (LEA21, Rochdale)
Lowest positive return		0.063 (LEA10, Blackburn)
Median		0.0996 (LEA2, Lancashire)
Number of LEA-specific returns in the range:	< 0.08	12
	0.081 – 0.090	11
	0.091 – 0.100	52
	0.101 – 0.110	41
	0.111 – 0.120	14
	0.121 – 0.130	4
	0.131 >	4
		138 (Total)

Table 3.3b Summary of the 138 LEA-specific returns to education obtained from OLS estimation of (3.7)

Equation (3.7) produces estimates of the return to schooling for 138 of the 148 LEAs in England and Wales. Table 3.3b presents a summary of these LEA-specific returns. A full listing of the local authorities and their individual estimated returns to schooling are provided in appendix B. All but one of these LEA-specific returns are positive ranging from 6.3% in LEA10 (Blackburn) to 18.5% in LEA21 (Rochdale), and are all highly significant. In performing a test of the potential equality between these two coefficients, an F statistic of 3.24 implies that the null hypothesis of equality may be rejected at the 10% level. The only negative estimate of the return to schooling is associated with LEA57 (Northamptonshire), although this coefficient is found to be statistically insignificant. The figures in table 3.3b show that the mean rate of return is 10%, which is also approximately equal to the median, represented by LEA2 (Lancashire). Overall, 96 out of the 138 LEA returns are within the range 9.1% to 11.0%. Given the distribution of the estimated returns to education across England and Wales described in table 3.3b, the second part of the statistical analysis attempts to determine whether differences in the quality of education play a role in determining the variation in these LEA-specific returns.

3.5.3 Estimated effects of quality on the LEA-specific returns to schooling

The second stage of the statistical analysis involves the estimation of equation (3.8) where the LEA-specific returns obtained from the first stage are regressed on groups of variables which include measures of the average level of school quality within each LEA. The main measures of quality used are the pupil-teacher ratio, expenditure per pupil, and average teacher salary. These variables were obtained from CIPFA and relate to the year 1970, which is when the NCDS cohort would have been in their first year of secondary education. Some additional variables, derived form the sweep of the NCDS taken at age 16, relating to school type are also included in the second stage regression. These variables capture the proportion of male pupils within each LEA who attended a grammar school and the proportion that attended an all boys school. The third group of variables represented in (3.8), denoted by *NBHOOD*, includes the proportion of pupils who received free school meals as a measure of the level of deprivation within each LEA. A measure of the density of population, obtained from CIPFA, is also included as a local neighbourhood variable. Finally, the LEA-specific returns are regressed on a set of family control variables (*FAMILY*) capturing the mean educational attainment of parents within the LEA, and the mean monthly family income. Any other geographic factors that may influence the estimated returns to schooling are captured by a set of 10 regional variables indicating the standard region in which the LEA is located.

Table 3.4 below presents the results obtained from estimating various versions of equation (3.8) which differ with respect to the number of control variables included. The dependent variable consists of the 137 positive LEA-specific returns to schooling obtained from the first stage, where the returns are expressed as a percentage. Due to concerns arising from using the estimated LEA-specific returns as the dependent variable in the second stage, equation (3.8) is estimated by weighted least squares with the weights being the inverse sampling variances of the estimated schooling coefficients obtained from the first stage. This estimation technique attaches more weight to the LEA-specific returns that were estimated with greater precision in the first stage.

Control Group	*Variable*	(1)	(2)	(3)	(4)
Q	*CIPFAPTR*	-0.144 (1.066)	-0.079 (0.578)	-0.088 (0.565)	0.0173 (0.112)
	CIPFASAL	-0.052 (2.247)	-0.054 (2.347)	-0.056 (2.243)	-0.0261 (0.921)
	CIPFAEXP	-0.005 (-0.424)	0.002 (0.131)	0.003 (0.253)	-0.002 (0.190)
TYPE	*MNBOYS*	-	0.103 (0.105)	0.058 (0.054)	0.862 (1.384)
	MNGRAM	-	1.851 (2.079)	1.648 (1.794)	1.467 (1.682)
NBHOOD	*MNMEALS*	-	-	1.160 (0.687)	0.487 (0.282)
	CIPFAPOP	-	-	0.006 (0.432)	0.008 (0.556)
FAMILY	*MNMEDUC*	-	-	-0.640 (1.527)	-0.386 (0.939)
	MNFEDUC	-	-	0.521 (1.381)	0.581 (1.542)
	MNFAMINC	-	-	0.005 (1.666)	0.003 (0.845)
AREA	*AREA2*	-	-	-	1.147 (2.999)
	AREA3	-	-	-	0.406 (1.040)
	AREA4	-	-	-	1.009 (2.400)
	AREA5	-	-	-	0.614 (1.504)
	AREA6	-	-	-	0.253 (0.599)
	AREA7	-	-	-	-0.413 (1.007)
	AREA8	-	-	-	-0.251 (0.571)
	AREA9	-	-	-	1.170 (3.207)
	AREA10	-	-	-	0.093 (0.171)
	constant	18.582 (4.463)	16.218 (3.816)	15.122 (2.989)	10.229 (1.933)
	R-squared	0.0769	0.112	0.1562	0.3261
	F (model)	3.69	3.31	2.33	2.98
	N	137	137	137	137

Table 3.4 Estimation of equation (3.8)
Dependent variable is the coefficient on ($S*LEA_l$) multiplied by 100

In the first column of table 3.4, the estimated LEA returns are regressed on only the three main measures of quality. It may be seen that the pupil-teacher ratio (*CIPFAPTR*) has the anticipated negative effect on the rate of return, although is statistically insignificant. The measure of the pupil-teacher derived from the NCDS (*NCDSPTR*) was then used in place of *CIPFAPTR*, but was also associated with a negative and insignificant coefficient. Contrary to expectations, both expenditure per pupil (*CIPFAEXP*) and average teacher salary (*CIPFASAL*) are both found to negatively affect the return to education, with the effect of teacher salary being significant at the 5% level. These results, therefore, offer limited support for the existence of quality effects and are similar to Card and Krueger's in the sense that when all three quality measures are entered collectively, most of the coefficients become insignificant. One potential reason for the observation of insignificant quality effects arises from the likely correlation between the quality variables, particularly between the two expenditure measures. Equation (3.8) was therefore re-estimated with the inclusion of the pupil-teacher ratio and either teacher salary or expenditure per pupil, but this was found to have little effect on the quality effects reported in column 1.[32]

The second column of table 3.4 introduces two additional variables reflecting the type of schools contained within each LEA. It may be the case that for a given level of quality, LEAs that place a higher proportion of its pupils in single sex or grammar schools are associated with a higher rate of return. This is because segregating pupils according to their gender or ability may generate peer effects which alter the performance of pupils within school. The results presented in column 2 suggest that LEAs with a high proportion of its pupils attending grammar schools (*MNGRAM*) are associated with significantly higher returns to education, holding the level of quality constant. This may provide some evidence to support the view that segregating pupils according to their ability is beneficial to individuals of all ability levels within the LEA. For the other school type variable, however, the proportion of pupils attending a single sex school (*MNBOYS*) appears to exert little effect on the return to education, suggesting that segregation by gender is not as effective as segregation by ability.

It is also possible that the coefficients reported in column 1 are biased due to the omission of additional variables that are correlated with both the return to education and quality. One possible factor is the proportion of pupils receiving free school meals, which is interpreted as a measure of social deprivation. LEAs with a relatively deprived population tend to receive higher funding and are therefore potentially observed as having higher expenditure per pupil. If some of this additional expenditure is used to provide free school meals, the quality of education is not necessarily higher than in LEAs receiving less funding. In addition, pupils from deprived areas may be associated with a weaker performance in school. The overall effect may then be that in deprived areas, higher expenditure per pupil is associated with a lower return to education, causing the coefficients associated with the quality variables to be biased downward. It may be seen in column 3 of table 3.4, however, that after controlling for the proportion of pupils receiving free school meals (*MNMEALS*), there is little change in either the magnitude or statistical significance of the quality coefficients.

The fourth set of control variables introduced into equation (3.8) relate to the mean characteristics of the families living in each of the LEAs. In studies that measure quality at the school level, it is often argued that the omission of family background variables will overstate the effects of quality. This is because parents with high income or high educational attainment

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[32] A regression that included *CIPFAPTR* and *CIPFASAL* produced coefficients and *t*-ratios of -0.127 (0.985) and -0.057 (3.043) respectively, while regressing the estimated returns on *CIPFAPTR* and *CIPFAEXP* produced results of -0.044 (0.339) and -0.215 (2.051) respectively.

may select the highest quality schools for their child to attend. In addition, having parents with a high level of educational attainment may raise an individual's performance in school. Under these circumstances, omitting variables relating to the characteristics of a pupil's parents may generate quality effects that are biased upward. This source of bias is likely to be most pronounced when including measures of quality and family background that are specific to individual pupils since parents are able to choose the best school for their child. When looking at quality and family background variables measured as LEA averages, however, the potential for biased quality effects is likely to be reduced. This is because high income parents are more likely to select the highest quality schools within their existing LEA, rather than locating themselves in an LEA where the average quality of schooling is higher. In this case, average family income within an LEA may not be highly correlated with the average level of quality, reducing the potential bias associated with omitting family income. Column 3 of table 3.4 includes three family background control variables that are measured as LEA averages- mother's educational attainment (*MNMEDUC*), father's educational attainment (*MNFEDUC*), and family income (*MNFAMINC*). Mean family income is found to positively affect the return to education and is significant at the 10% level, but the opposing effects associated with parental education are both statistically insignificant. After controlling for these variables, it may be seen that there is little alteration in the coefficients associated with the three measures of quality, suggesting that the omission of family background variables in columns 1 and 2 does not generate biased quality effects.

The final column in table 3.4 introduces a set of area variables indicating the standard region in which each of the LEAs is situated.[33] These variables are designed to capture any other additional local environment factors affecting rates of return that are not covered by the neighbourhood variables included in column 3. The inclusion of these variables lowers the magnitude and statistical significance of the coefficients attached to the pupil-teacher ratio and teacher salary variables, suggesting that the exclusion of regional controls in columns 1-3 may introduce a source of bias into the quality effects. At a significance level of 5%, an *F*-test rejects the hypothesis that the additional area controls are jointly insignificant, meaning that the inclusion of these variables does significantly raise the explanatory power of the model compared to that estimated in column 3.[34] Those LEAs located within the Northern region (*AREA2*), the North Midlands (*AREA4*), and the Midlands (*AREA9*) are associated with a higher rate of return to education relative to the excluded North Western region.

[33] The eleventh standard region identified in the earnings equation, Scotland, is not applicable here since only LEAs located in England and Wales are considered.
[34] The *F*-statistic is 3.28 which has a p-value of 0.0013.

3.5.4 Additional estimations

The results from estimating the two stages of the statistical analysis presented in sections 5.2 and 5.3 were obtained using the date of labour market entry for the measure of years of schooling. In order to check the robustness of the estimated coefficients reported in tables 3.3a to 3.4, the two stages were re-estimated using the alternative measure of schooling described in section 4.1. The alternative measure involves interacting the number of years spent in education up to age 23 with the LEA dummy variables, and then including a set of nine dummy variables capturing the highest qualification obtained between ages 23 and 33.[35] Separating educational attainment in this way may be appropriate since the return to any education accumulated in later years is unlikely to be determined by the LEA in which the individual was educated at age 11. The results from estimating equation (3.7) using this alternative measure of schooling were found to be similar to the results shown in tables 3.3a and 3.3b. LEA21 (Rochdale) was again found to be associated with the highest rate of return of 19.1%, while LEA10 (Blackburn) had the lowest return of 7.1%. The mean rate of return across the 138 LEAs was found to be 10.4%, which is comparable with the mean value of 10.0% obtained when schooling was measured by the date of labour market entry. In the second stage of the analysis, the coefficients and statistical significance of the quality measures were also found to be similar to those shown in table 3.4, column 1. For example, the coefficient associated with the pupil-teacher ratio was estimated to be -0.112 with a *t*-ratio of 0.870.[36] Despite the fact that the measure of schooling used in estimating the model in section 5.2 is unconventional, the results obtained are not substantially altered when an alternative measure of educational attainment is used in the analysis.

In producing the LEA-specific returns to schooling in section 5.2, the equation was estimated by OLS without the inclusion of controls for ability. The reason for doing this was that when estimating the average rate of return across all LEAs in section 5.1, it was found that the effects of the various sources of bias tended to offset each other. Although the average rate of return for all LEAs is largely unaltered after controlling for each of the sources of bias, it is not necessarily the case that each of the LEA-specific returns is unaltered. In this case, the distribution of the estimated LEA-specific returns may differ after controlling for each source of bias compared to the distribution estimated in section 5.2 where no attention is given to the potential forms of bias. Since these estimated returns are carried over to the second stage of the statistical analysis, the estimated quality effects may be sensitive to any changes in the LEA-specific returns occurring as a result of correcting for ability bias, measurement error, or

[35] See appendix B for a description of these dummy variables.

[36] For *CIPFASAL* and *CIPFAEXP*, the coefficients and *t*-ratios were -0.042 (1.914) and -0.007 (0.556) respectively.

endogeneity. In order to explore this, equation (3.7) was re-estimated with the inclusion of a set of dummy variables capturing ability at age 11. The results were found to be broadly similar to those reported in tables 3.3a and 3.3b, with LEA21 (Rochdale) being found to have the highest rate of return to schooling of 16.3%, and LEA10 (Blackburn) observed with the lowest positive return of 3.4%. As expected, after controlling for ability, the estimated rates of return are smaller in magnitude compared to those summarised in table 3.3b. Using these LEA-specific returns in the second stage was found to make little difference to the magnitude and significance of the estimated quality effects.[37]

The results presented in sections 5.1 to 5.3 are all produced from estimating the various equations of the statistical framework using a sample of 1576 males. In order to examine the effect that school quality has on the return to education among females, the equations were re-estimated for a sample of women extracted from the NCDS. By following exactly the same steps as for men, a sample of 760 females was constructed who were educated in 130 of the 148 LEAs in England and Wales. The mean LEA rate of return was found to be 8.1%, ranging from 0.8% in LEA54 (Lincoln) to 23.4% in LEA21 (Rochdale). In the second stage, however, the magnitude of the quality effects were found to be almost zero and none were close to statistical significance. One of the problems in repeating the statistical analysis for women is that the sample size is relatively small since at age 33 some women will be out of the labour force for child raising purposes. When estimating the first stage of the statistical analysis, therefore, a selection term should be included for those who are observed as being in employment at age 33. For completeness, the first stage earnings equation should also contain the number of years of non participation accumulated by age 33 as an explanatory variable alongside the number of years of labour market experience.

3.6 Conclusion

The quality of education in the UK has become one of the main political issues in recent years. It is widely believed that more resources need to be directed towards the education system in order to raise the performance of students and improve their subsequent prospects within the labour market. Evidence from the US would appear to offer some support for this view in that some studies have detected a link between the quality of education and labour market earnings. For the UK, however, recent studies undertaken using the NCDS have found no evidence to support the view that the quality of education positively affects earnings. In

[37] After controlling for omitted ability bias, the LEA-specific returns may still be biased due to measurement error or endogeneity. In this case, it would be necessary to instrument the number of years of schooling for each of the 148 LEAs. IV estimation is usually only undertaken when a single estimate of the return to schooling is obtained for all individuals in the sample, as in section 5.1.

these studies, measures of quality are included as additional explanatory variables within a conventional earnings equation. This approach hypothesises that higher quality raises earnings for a given level of educational attainment. There are alternative ways, however, for modelling the influence that school quality has on future labour market earnings. The empirical analysis undertaken in this study also uses the NCDS, but follows a different approach to the existing UK literature. A simplified version of Card and Krueger's (1992) approach is followed where individual estimates of the rate of return to schooling are obtained for each of the local education authorities in England and Wales. These estimated returns are then regressed on three measures of quality and a set of additional variables capturing the environment within each LEA. Within this framework, therefore, the effect that quality has on labour market earnings is believed to operate through the rate of return to education. The quality of education may then be seen as altering the slope of the earnings-schooling relationship rather than its vertical positioning.

The results obtained from the first part of the statistical analysis finds that the rate of return to education does significantly vary across LEAs. For males, the rate of return is found to range from 6.3% to 18.5%, with the mean value across all LEAs being 10.0%. In the second stage, however, no evidence is found for the existence of significant quality effects operating in the anticipated direction. The effects that the pupil-teacher ratio and expenditure per pupil have on rates of return are found to be insignificant. In some specifications of the model, average teacher salary is actually found to exert a significantly negative influence on an LEA's rate of return to schooling. The inclusion of additional LEA control variables, such as the composition of schools, the level of deprivation, and family wealth appear to have little effect on the magnitude and statistical significance of the quality effects. It is difficult, however, to fully control for local environment factors due to a lack of data relating to the LEA level, which weakens the second stage of the analysis. By including regional dummies, it would appear that the region in which the LEA is located does play a role in determining the return to education. The inclusion of these variables also reduces even further the effect that quality has on the LEA-specific returns. This may imply that there are additional geographic factors which are important in explaining the returns to education, and which are also correlated with the level of quality.

The results from this study would therefore appear to reinforce the findings of existing studies of the effects of school quality on labour market outcomes using the National Child Development Study cohort. Previous research has indicated that measures of school quality exert little direct impact on earnings, whereas the results presented in this study also suggests that quality does not have an indirect effect on future earnings operating through the rate of return to schooling. This may imply that policies aimed at raising the quality of education, such as recruiting additional teachers in order to lower class sizes, would be expected to be ineffective in terms of raising labour market prospects. It is important to recognise, however, that the NCDS cohort received their secondary education during the 1970s and any relationship that existed between the quality of their education and future earnings may not hold for those currently within the education system. As in the existing UK research on the effects of quality, this study has examined the extent to which the quality of secondary education influences subsequent labour market earnings. It may well be the case, however, that higher quality education exerts a greater impact on individuals during their years of primary education.

Chapter 4 Estimating the Wage Effects Associated With Labour Mobility in Britain

4.1 Introduction

The theory of human capital predicts that following entry into the labour market, workers will continue to invest in additional productivity enhancing skills while employed within a job. Some of these on-the-job investments will be in general human capital, which raises productivity within all firms. Other investments may be in specific human capital which only increases the level of productivity in the current firm. Theoretical models generally predict that the incentive to invest in general human capital diminishes with experience in the labour market, while the incentive to invest in specific skills declines with tenure in the current job. In order to test the empirical validity of these predictions, economists often use years of labour market experience and job tenure as explanatory variables when analysing the determinants of earnings at a point in the life cycle. Evidence from numerous studies suggests that earnings do increase with both experience and tenure, but at diminishing rate. The existence of concave experience-earnings profiles in particular, is often interpreted as providing strong evidence in support of the theory of human capital accumulation. There are, however, alternative explanations for why a worker's earnings may increase at a diminishing rate as they accumulate experience in the labour market. Theories of job mobility are capable of generating experience-earnings profiles that are concave in nature independently of any investment in human capital. In this case, part of the positive returns associated with experience that have been detected in the empirical literature may be attributable to the wage gains arising from job mobility. The statistical analysis contained within this chapter attempts to analyse the importance of job mobility by investigating the effect that switching jobs over the period 1991-1994 has on both the positioning and slope of the earnings profile.

Analysing the wage effects of switching jobs is an interesting area of research since mobility would appear to be an important aspect of an individual's experience within the labour market. Workers are rarely observed as remaining on the same job from the time of leaving school until the date at which they retire. Instead, there is a tendency for workers to undertake a series of job changes throughout their working lives. Over the last two decades, the field of labour economics has attempted to gain a deeper understanding of the issues surrounding job mobility from both a theoretical perspective and as an empirical application. Although the theoretical literature suggests that there are a number of ways of viewing the mobility process, all of the approaches are based on the notion that a worker will only have an incentive to switch jobs if such a job change raises the expected present value of lifetime earnings. In the long run, therefore, the mobility wage gain is predicted to be positive. The manner in which this positive long run gain is generated, however, is less clear cut. For example, some theories of mobility suggest that when switching jobs, a worker receives a once and for all wage increase which induces an upward shift in their earnings profile. Alternatively, the positive long run gain may arise as a result of switching into a job associated with a higher rate of on-the-job wage growth, causing the earnings profile to become steeper. The challenge from an empirical point of view is to not only estimate the magnitude of the total mobility wage gain, but to also attempt to gain an understanding of the way this gain is generated. The empirical analysis undertaken in this study uses data from the British Household Panel Survey (BHPS) in order to estimate the total wage gain received by individuals who switch jobs over a three year period. The methodology adopted also enables an attempt to be made at identifying the part of the total gain that is attributable to a shift in the earnings profile and the part due to the movement onto a steeper wage profile.

One of the most important issues that needs to be addressed within any empirical study of mobility is that of selectivity bias. Estimates of the mobility wage gain are based on a comparison of the growth in earnings between job movers and job stayers over a particular period of time. Unobservable differences between these two groups, however, may mean that the wage growth of stayers is not a suitable approximation of the wage growth movers would have received had they not moved. Failure to take account of such sample selection effects is likely to lead to an inaccurate estimate of the mobility wage gain being obtained. Existing empirical work generally employs two techniques for correcting for this source of bias. The most common method is to estimate separate wage growth equations including selectivity terms for movers and stayers and then derive the mobility gain by calculating the wage growth a worker with mean characteristics would earn as a mover and as a stayer (Holmlund 1984). An alternative approach exploits panel data to compare the wage growth of those who switch jobs in the current period with those who experience a job change in the next period. These two groups of individuals are hypothesised to be similar in terms of their unobservable characteristics (Mincer 1986). An estimate of the mobility wage gain may then be derived from estimating a single wage equation that includes dummy variables for these two groups of workers (Abbott and Beach 1994). It is an extended version of this dummy variable approach that is applied to the BHPS in order to estimate the total mobility wage gain received over a three year period and the form that this gain takes. The results obtained suggest that male employees who switch jobs either within the same firm or across firms during the period 1991 to 1994 experience 10.8% higher wage growth than similar individuals who remain on the same job during the three year interval. In addition, approximately three-quarters of this gain is attributed to the movement onto a steeper earnings profile following a job change. For women, the total wage gain over the same period is calculated to be 9.3%, with half of this gain being due to an increase in the rate of on-the-job wage growth in the new job. The empirical analysis also provides some evidence for the existence of sample selection effects which need to be controlled for when deriving an estimate of the wage gain associated with labour mobility.

In the remaining sections of this chapter, section 2 summarises some of the main theoretical approaches to analysing the wage effects associated with job mobility. By drawing on these theoretical contributions, it is possible to gain an understanding of why the earnings profile may shift or change slope following mobility. Section 3 then reviews some of the existing empirical literature relating to estimating the mobility wage gain. Two studies are focused on as a way of outlining the two methodologies that have been used for analysing the effect that changing job has on earnings. The fourth section of the chapter then describes the methodology adopted within this study, which is essentially an extension of the dummy variable framework used by Abbott and Beach (1994). In section 5, a description is given of how the BHPS data is used to estimate a wage change equation over the period 1991-1994. Some summary statistics are also presented to illustrate the mobility behaviour of individuals over a period of time. Section 6 reports the results obtained from the statistical analysis, while the final part of the chapter considers any conclusions that may be drawn from the study.

4.2 Theoretical approaches

There are numerous models within the theoretical literature analysing the determinants of job mobility and the subsequent effect that such mobility has on the earnings of an individual over time. Although the models approach the issue of mobility in differing ways, all envisage a labour market characterised by some degree of heterogeneity or imperfect information. It is widely assumed that there exists a range of jobs in the labour market, arising from the fact that firms differ in the tasks that they require workers to perform. Each individual worker differs in their ability to perform these tasks required for each of the available jobs. Heterogeneity is also likely to exist across workers in the sense that for any given job, two individuals may differ in their productivity on that job. Some models of mobility also introduce the assumption of imperfect information, with firms initially being uncertain of the actual productivity associated with a new recruit to the job. Introducing these assumptions has the implication that mis-matches may occur in the labour market where workers are initially not employed in the jobs in which they are most productive. Job mobility then provides the mechanism for the market to move towards an efficient allocation of resources where workers locate themselves in the jobs that maximise their productivity. Without the assumptions of imperfect information and heterogeneity, upon entry into the labour force, workers will immediately settle in the jobs in which they are most productive and remain on that job until retirement.

In order to explore the issues surrounding job mobility, research within the theoretical literature generally refers to three main approaches- job search, job matching, and on-the-job training. It is important to emphasise, however, that these are considered as being non competing approaches in the sense that each one contributes to an overall understanding of the mobility process. In order to analyse the wage effects associated with mobility from an empirical point of view, it is likely that the ideas embodied within these approaches would have to be combined. Although the three approaches all predict that the mobility wage gain will be positive in the long run, they provide differing insights into the way in which this long run gain is generated. In particular, the job search approach implies that mobility shifts the earnings profile upwards, while the matching and training approaches imply that the profile may become steeper following a job change. Since the empirical analysis undertaken in this study attempts to identify the existence of these wage effects, sections 2.1 to 2.3 below briefly describe the three main approaches to mobility and the implications that they have for the path of earnings following a change of job.

4.2.1 The job search approach

Within the set of models described by Jovanovic (1979) as "pure search good" models of job change, the most commonly referred to in the mobility literature is that of Burdett (1978). One of the most important assumptions of this approach is that a worker's productivity remains constant while employed within a particular job. This implies that the earnings profile remains horizontal for the duration of any job. The assumption of heterogeneity, however, suggests that the worker is associated with a distribution of productivity and wages, reflecting their differing ability to perform the tasks required for each of the jobs available. In a way, the worker may be seen as entering the labour market with a stock of human capital, which remains constant over time, and firms differ in the level of productivity that they can extract from the worker. If upon entry into the labour market, the worker accepts the first job made available to them, their initial wage may be seen as a random draw from a distribution of wage offers reflecting their differing performance in all of the available jobs. Once employed within the first job, the individual is able to engage in search activity. Each firm the worker approaches offers the individual a wage that is related to their productivity within the firm. Some wage offers will be greater than the current wage and others will be lower than the wage currently received. The more intensely the worker searches, the faster is the arrival rate of wage offers. If the worker successfully identifies a job offering a higher wage, they will have an incentive to switch jobs if the present value of the earnings stream in the alternative job exceeds that associated with the current job, after allowing for any costs incurred as a result of switching jobs. The existence of these costs implies that the wage offer in the new job needs to be significantly greater than the current wage to induce an individual to switch jobs.[1] This simple search approach, therefore, predicts that mobility exerts a positive effect on lifetime earnings. The mobility wage gain in this case arises as a result of a vertical shift in the earnings profile, which remains flat while employed within any particular job. Figure 4.1 below illustrates the earnings profile (*ABCDEF*) for an individual who enters the labour market at *S* and switches jobs in periods t_1 and t_2.

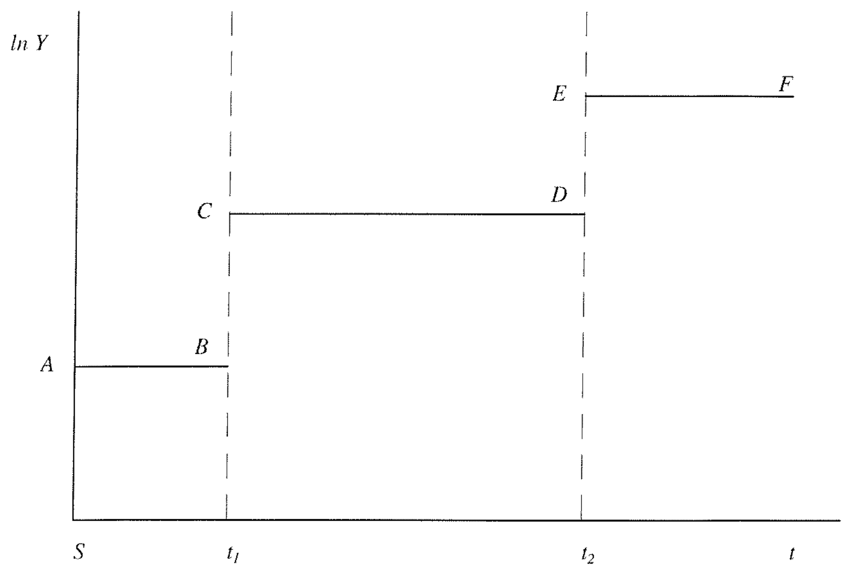

Figure 4.1 The pure search approach to mobility

A common finding in the empirical literature relating to the theory of human capital is the observation of earnings profiles that are concave with respect to years of labour market experience. In human capital theory, this finding is explained by investment ratios that are positive in any period but which decline with experience. Even though in the search model

[1] With zero mobility costs, workers would only require a marginal increase in the wage to provide them with an incentive to move.

described previously, both productivity and wages remain constant on any job, the search approach is capable of providing an alternative explanation for the existence of concave earnings profiles. Within the search approach, more experienced workers are not associated with higher wages because they have become more productive over time, but because they have had more time to locate themselves into higher paying jobs. With each job change, the worker moves further along the wage offer distribution, leaving them with fewer jobs in which it will be worthwhile for them to move into in the future. If they continue searching with the same intensity, the probability of switching jobs is then expected to decline with experience. Even if the worker does identify a superior alternative, it is also likely that the wage gain associated with such a job change will be lower than the gains that were made earlier in the life cycle. As individuals accumulate more experience, it is also possible that search intensity falls and mobility costs rise, which further influences the propensity to move. With the probability of moving and the wage gains associated with mobility declining with experience, the earnings profile in figure 4.1 begins to trace out the conventional concave shape. The search approach may, therefore, be seen as providing an alternative explanation for the concave earnings-experience profile that is observed in the empirical literature.

4.2.2 The on-the-job training approach

The on-the-job training approach differs from the search approach in that it is no longer assumed that a worker's productivity remains constant while employed in a particular job. One of the main elements of the theory of human capital is that productivity increases with tenure on a job as a result of the accumulation of specific human capital. Rising productivity then gives the potential for on-the-job wage growth as the firm and worker share the returns generated by specific human capital investments. The earnings-tenure profile is predicted to be concave if the incentive to invest in specific human capital is greatest when the worker starts a job, but then gradually declines with the accumulation of job tenure. New recruits to a job are therefore expected to be on the part of the earnings profile that is relatively steep, while those who have been employed in the job for many periods will be associated with a flat wage profile.

In the version of the training approach considered by Mortensen (1988), an individual may be willing to accept a pay cut when switching jobs in order to receive a higher rate of wage growth in the new job. The intuition behind this result is that the rate at which earnings grow on a particular job is related to the amount of tenure accumulated on that job. A worker who has been employed in a job for a long time will receive little additional investment in specific human capital and, therefore, expect their wage profile to be relatively flat if they continue in the same job. If the same worker were to switch jobs, however, their level of tenure resets to zero and they will receive a high level of specific human capital investment, which will in turn, imply that they will be faced with a steep earnings profile.[2] In each period after the job change occurs, the rate of wage growth the worker receives in the new job will always exceed that of which they would have received had they continued in the initial job. This is because in all subsequent periods, the level of tenure in the new job will always be lower than the tenure that would have been accumulated in the previous job. Following a job change, therefore, the worker may move onto a wage profile that is always steeper than the profile they would have been on had they chosen not to move.

When a worker does quit a particular job, the specific human capital accumulated on that job is lost, leaving them with just their stock of general human capital to transport into the new job. Assuming for the moment that the stock of general skills remains constant over time, the starting salary offered in the new job will depend on the level of productivity that the new firm can extract from the worker's skills. This means that the starting wage associated with the new job could be greater or less then the wage that was received at the end of the previous job. Although the worker loses their wage enhancing specific skills when they leave one job, it is possible that they switch into a job that pays a higher rate of return on their general skills than the previous job paid. In this case the starting salary in the new job will not fall all the way back to the wage that was initially received in the previous job. A likely outcome is that the starting wage in the new job will lie somewhere between the starting wage and final wage received in the previous job. An alternative outcome, however, is that the worker identifies a new job offering a return on their general skills great enough to create a starting salary on the new job that exceeds the final wage received in the previous job. The instantaneous effect of switching job, therefore, may see the worker's earnings either increase or decrease relative to the final wage received in the previous job. Once employed in the new job, however, the earnings profile is predicted to become steeper since the worker has low tenure on that job and so receives a relatively large quantity of specific human capital investment. Under these circumstances, an individual maximising the present value of future

[2] Mortensen assumes an infinite time horizon, which is capable of generating the result that when a worker switches into a new job, tenure resets to zero, and the rate of specific human capital also returns to an initial value associated with zero tenure. If this investment profile is the same across jobs, new recruits always face a steep earnings profile as a result of a high rate of human capital accumulation. With a fixed retirement date, however, it is likely that the entire tenure-specific human capital profile decreases with age. When starting a new job, a worker will actually invest in less specific human capital at the start of the new job compared to the start of the previous job since their age has increased. This implies that the rate of growth of earning in the early years of a job falls with each new job that the worker moves into as a result of their age increasing.

earnings would be willing to accept a wage cut at the point of job change in the knowledge that earnings in the new job will eventually catch up with and overtake the earnings they would have received had they continued in the previous job. Mortensen argues that at the point of job change, workers will have a reservation wage offer that leaves the individual indifferent between staying on the current job and switching into a new job. This reservation offer will always be lower than the current wage. Since any actual wage offer greater than the reservation offer will be accepted, the starting salary in the new job could be either greater or less than the wage received at the end of the previous job. Overall, therefore, mobility will cause the earnings profile to become steeper, but could either shift up or down at the point of job change.

4.2.3 The job matching approach

Another group of models used to analyse labour mobility consider a job as a "pure experience good".[3] As in the search approach, most models assume that a worker's actual productivity on a given job remains constant, which implies that there is no additional investment in valuable human capital once employed within a job. The most important assumption of the matching approach is that there may initially be uncertainty over a worker's actual productivity within a particular job. As job tenure is accumulated, additional information is revealed relating to the worker's actual productivity on the job. In the light of such new information, the firm makes adjustments to the wage paid to the worker. This then gives the opportunity for wages to grow on a job even though actual productivity remains constant.

The matching approach may be viewed as an extension of the search approach described previously. Heterogeneity implies that workers face a distribution of actual productivity arising from their differing ability within the jobs available in the labour market. The presence of imperfect information, however, implies that upon entry into a particular job, an individual's actual productivity on that job is not known with certainty. The starting salary offered by the firm is based on the expected value of productivity given the information available at the time the job commences. As job tenure is accumulated, the firm gains new information relating to the worker's actual productivity. This additional information enables the firm to form a new estimate of actual productivity, which in turn, leads to an adjustment of the wage paid to the worker. Under these circumstances, a worker may see their earnings either increase or decrease in a given job. A worker whose actual productivity on the job is relatively high can expect a positive rate of wage growth while employed on the job. Due to

[3] This terminology is used by Nelson (1970) and Jovanovic (1979).

the assumptions that Mortensen and others make concerning the way information is accumulated, the rate at which earnings grow is greatest at low levels of job tenure. This produces an earnings-tenure profile that is concave for those who remain on the same job. Positive on-the-job wage growth is therefore observed as a result of sample selection bias. This bias arises because only those individuals who are relatively productive on a particular job will remain on that job. Those in poor matches, where earnings decline on the job, or grow at a slow rate, are the ones who are most likely to quit the job that they are currently employed in.

The main implications of the job matching approach described by Mortensen are the same as that of the training approach- workers will be willing to accept a pay cut when switching jobs in order to move into a job with a higher rate of on-the-job wage growth. An individual who has accumulated a large amount of tenure on a job will be associated with a low rate of on-the-job wage growth. This is because with high tenure, the firm's estimate of the worker's productivity will be close to the actual value. Any further wage adjustments that occur following the arrival of new information are likely to be small. If the individual were to switch jobs, however, there is the potential for the rate of on-the-job wage growth to be relatively high. When starting the new job, there may initially be great uncertainty over actual productivity which implies that as new information arrives, future earnings may rise considerably above or below the starting wage.[4] The probability of receiving a high rate of on-the-job wage growth is therefore greater in an alternative job than remaining in the current job, but there is also a higher probability of incurring wage losses in a new job. Mortensen argues that because workers are insured against negative wage growth as a result of the option to quit to non employment, workers will be willing to accept the risk associated with the path of future earnings in the new job. With the possibility of moving onto a steeper earnings profile in the new job, individuals maximising future incomes would be willing to move into a job that pays a starting wage less than the wage currently received. As in the training approach, a reservation offer will exist that leaves the worker indifferent between quitting and remaining on the current job. Any starting wage offer on a new job that exceeds this reservation offer will be accepted. In this case, the starting wage offer will be drawn from a distribution of offers reflecting firms initial assessments of productivity rather than actual productivity.

[4] The process of information accumulation is assumed to be the same across all jobs. Once an individual quits a job, all information accumulated on that job is lost and the process starts again in the new job. Other matching models assume such information is valuable across firms, for example Eriksson (1991) and Liu (1986).

4.2.4 Summary of the main theoretical issues

The aim of this section has been to describe how different theoretical tools may be combined in order to develop an understanding of the effect that switching jobs has on the earnings profile. The ideas embodied in the training and matching approaches may be referred to when describing how earnings grow while employed in a particular job, whereas the search approach provides an insight into how the starting wage on a new job compares to the final wage received on the previous job. Whatever theoretical model that is referred to, in the long run it is expected that the mobility wage gain is positive since workers will only switch jobs if it enhances their lifetime earnings. The search, training, and matching hypotheses suggest that part of this gain is due to a shift in the earnings profile following a job change and another part due to a change in the slope of the profile. Either of these individual wage effects could be negative even though the total mobility wage gain is positive. For example, in Mortensen's version of the matching approach, the earnings profile may shift down following mobility but become steeper. In other versions of the matching approach, such as Eriksson (1991), which are based on slightly different assumptions, the earnings profile is predicted to shift up following a job change, but become flatter.[5] In both cases, the overall wage gain associated with mobility is positive although the way that this gain is generated differs. For this reason, it would appear to be an important empirical issue to go beyond estimating the magnitude of the long run mobility wage gain and investigate how this gain arises in terms of shifts and changes in the slope of the earnings profile.

4.3 Review of the existing empirical literature

There have been numerous studies undertaken, mainly using US and Canadian data, that have analysed the factors determining labour mobility and the corresponding effect that such mobility has on earnings. Most of these studies provide an estimate of the total wage gain received by individuals who switch jobs at some point over a particular time interval. In general, the issue of whether the total wage gain arises because of a shift in the earnings profile or a change in slope is not directly considered. Instead, the focus of attention in the existing empirical work is to estimate the total mobility wage gain while controlling for the effects of selectivity bias which are likely to be present when comparing two groups of individuals such as job movers and stayers. There are two main methods for addressing the

[5] Eriksson assumes that information relating to productivity on jobs is endogenous in that it is obtained as a result of investing in general human capital. This information may then be used to assess productivity in all jobs and not just the job in which the worker is currently employed. Once the job where productivity is maximised is identified, earnings rise at the point of job change, but the rate of growth of earnings falls since the incentive to invest in human capital for informational purposes declines.

issue of selection bias within the empirical mobility literature. The purpose of this section is to review two particular studies as a way of discussing the relevance of sample selection effects to the issues surrounding mobility and the techniques that may be adopted to control for such effects when estimating the mobility wage gain.

The ideal of way of accurately estimating the mobility wage gain would be to compare the change in wages between two points in time for an individual who switches jobs with the wage change that the same individual would receive had they stayed on the original job throughout. This is not possible, however, since the observed change in earnings is conditional on the worker's mobility decision. The wage change associated with moving is only observed for those who actually move, while the wage change associated with staying is only observed for those who do not switch jobs. When estimating the mobility wage gain, therefore, it is necessary to find a suitable approximation for the change in wages a job mover would have received had they chosen to remain on the initial job. The most obvious choice would be to use the change in wages received by a stayer who is identical in terms of their observable characteristics. The difference in the wage growth of two individuals who are observationally identical except for their mobility status could be interpreted as an estimate of the mobility wage gain. A potential problem with this estimate is that the groups of movers and stayers may be associated with different unobservable characteristics, which also influence wage growth. For example, it could be the case that stayers have higher unobservable ability which increases the rate at which wages grow when they remain on a particular job.[6] A mover with similar observable characteristics may not have similarly high unobservable ability and so would not have received as high a rate of on-the-job wage growth had they remained on the job. In this case, the on-the-job wage growth of stayers would overstate the growth in earnings an observationally similar mover would have received had they not moved. The implication of this is that when simply comparing the change in wages of movers and stayers, the estimate of the mobility wage gain may be understated. It is these differences in unobservable characteristics between the groups of movers and stayers that introduces a potential source of bias into the estimate of the mobility wage gain.

The existence of unobservable characteristics associated with the groups of movers and stayers therefore implies that the rate at which wages grow on any job is different for the two sets of workers. In general, it would be expected that stayers receive a higher rate of on-the-job wage growth than the group of movers would have received had they not switched jobs.

[6] Those with higher ability may invest in more general human capital or receive greater investment in specific human capital which increases the rate at which wages grow on the job.

This is because the workers who are observed as staying on the job are presumably the ones who had the most to gain by remaining on the job. The higher rate of on-the-job wage growth associated with these individuals could be due to the fact that stayers are already employed within a good match, or have higher levels of innate ability, both of which are unobservable factors. The wage change of stayers would then overestimate the wage change movers would have received had they not moved. It is entirely possible, however, to argue that the selectivity bias runs in the opposite direction in that it is the group of movers who are associated with higher unobserved ability. In this case, if the group of movers could be observed as remaining on their initial jobs, their earnings profile would be steeper than that of observationally equivalent stayers. The implications of this scenario for the theoretical predictions discussed in section 2 are potentially serious. In the job matching and on-the-job training approaches, individuals who switch jobs are predicted to move on to a steeper wage profile. If movers are also associated with higher unobservable ability, however, the observation of a wage profile that is steeper relative to stayers could be entirely due to unobservable ability effects and not as a consequence of mobility. Under these circumstances, too much of the observed difference in the wage growths of movers and stayers would be attributed to mobility, leading to the mobility wage gain being overstated.

The existence of unobservable characteristics may therefore lead to an inaccurate estimate of the mobility wage gain being obtained when simply comparing the change in earnings of movers and stayers over a given period of time. The estimated gain could be either overstated or understated depending on the direction of the selectivity bias. Existing empirical studies attempt to estimate the mobility wage gain by comparing the change in earnings over a period of time of movers with stayers, after controlling for the bias associated with differing unobservable characteristics between the two groups of workers. As will be seen below, Holmlund (1984) and Abbott and Beach (1994) present two different methodologies for estimating the mobility wage gain in the presence of selectivity bias. It is generally found that the mobility wage gain is positive, and is greater than the gain obtained when no allowance is made for selectivity effects between movers and stayers. In other words, those who stay in their jobs are usually found to have greater wage growth than movers would have received had they not moved, although the effect is often insignificant.

One of the most commonly referred to empirical studies within the mobility literature is that by Holmlund (1984).[7] Using data from the 1968 and 1974 Swedish Level of Livings Surveys, Holmlund attempts to estimate the total wage gain received by workers who switch jobs at some point during this time interval. In the model considered, it is assumed that an individual earns an initial wage and faces the decision of whether to remain on the current job or switch into an alternative. The two jobs differ in their rates of on-the-job wage growth, so if the individual switches jobs, they may be seen as moving onto a steeper earnings profile. Figure 4.2 below provides a simple representation of Holmlund's approach for an individual who switches job at some point fractionally after 1968. In a way, figure 4.2 may be interpreted as being a special case of the matching and training approaches where there is no vertical shift in the earnings profile following mobility, only an increase in its gradient.[8]

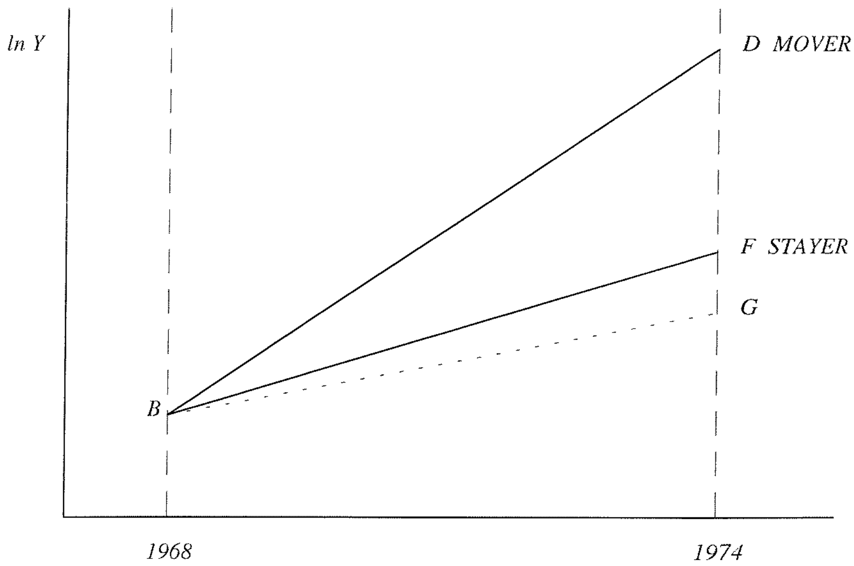

Figure 4.2 Holmlund's estimate of the mobility wage gain

In order to calculate the mobility wage gain, Holmlund estimates separate wage change equations over the 1968-1974 period for those who switch jobs and for those who remain on the same job. The possible existence of sample selection effects, however, may mean that the coefficients within a conventional wage change equation are biased. If it were the case that stayers possess unobservable characteristics that enhance their on-the-job wage growth, such

[7] A similar empirical methodology is used by Borjas and Rosen (1980), Kidd (1991) and Simpson (1990).

[8] In section 2 it was discussed how there exists a reservation offer that lies below the current wage. Any wage offer from a new job that exceeds this reservation offer is accepted. The starting salary in the new job could then be greater than, less than, or exactly equal to the current wage received.

as high ability, then the coefficients associated with the observable characteristics within the stayers' wage change equation would be biased upwards. Taking the mean observable characteristics of the sample of movers and then applying them to the stayers' wage equation would tend to exaggerate the estimate of the change in earnings a mover would have received had they stayed. When this estimate is then compared to the actual change in earnings received by movers, the mobility wage gain will be understated.

As a way of correcting for the potential upward bias of the coefficients associated with the observable characteristics within the stayer and mover wage equations, Holmlund uses Heckman's (1979) procedure for sample selection effects. This essentially involves re-estimating the stayer wage equation while controlling for factors such as high unobservable ability in order to obtain consistent coefficient estimates for the observable characteristics. Using this corrected version of the stayer wage equation, a stayer with mean observable characteristics would be predicted to have lower wage growth than when these mean observable characteristics are applied to the uncorrected wage equation. By removing the wage enhancing effects associated with unobserved ability, the earnings profile of stayers may be represented by the additional flatter profile, *BG*, in figure 4.2. In estimating the unbiased version of the stayer wage equation, Holmlund finds evidence for the existence of sample selection effects. The estimated coefficient on the selectivity term in the corrected stayer wage equation implied that those who remain on their jobs would receive higher wage growth than similar movers would have received had they not moved. This suggests that the observed profile associated with stayers is steeper than the profile movers would have been on had they not moved. This highlights the need to estimate the version of the stayer wage equation that corrects for sample selection effects when estimating the gains associated with job mobility. In order to derive an estimate of the mobility wage gain, Holmlund applies the mean observable characteristics of the sample of movers to the corrected stayer equation in order to obtain an estimate of the wage growth a mover would have received during the 1968-74 period if they had not changed jobs. This hypothetical wage growth is then compared to the actual mean observed wage growth of movers. By undertaking these calculations, Holmlund finds that the average annual rate of wage growth for movers is 2.3% higher than the growth rate they would have received had they not switched jobs.

The estimate of the mobility wage gain obtained by Holmlund may be viewed as a long run estimate. The theoretical issues discussed previously suggested that part of the total wage gain is due to a shift in the earnings profile and another part due to a change in slope of the profile. If, as in figure 4.2, mobility is assumed not to induce a shift in the wage profile, the

2.3% per annum gain calculated by Holmlund would reflect the gains made by movers as a result of moving onto a steeper wage profile. If it were the case, however, that the earnings profile also shifted up following a job change, the 2.3% per annum gain would incorporate both the wage gain arising from a shift in the earnings profile and the wage gain associated with a greater rate of on-the-job wage growth. Most existing estimates of the mobility wage gain include both the gains arising from shifts and changes in slope of the earnings profile and so may therefore be interpreted as longer run estimates. The next challenge from an empirical point of view is take an estimate of the total mobility wage gain and attempt to determine how much of this gain is due to a rise in earnings that occurs at the point of job change and how much is attributable to a faster rate of on-the-job wage growth in the new job.

There exists a second group of studies within the empirical literature that adopt a different methodology in order to estimate the wage gains associated with job mobility. These studies estimate a single wage change equation for all individuals within the sample and incorporate a dummy variable capturing whether the worker is a mover or a stayer. The coefficient on this dummy variable then gives the difference in the change in earnings between those who actually move and those who actually stay. This is unlikely to provide an accurate estimate of the mobility wage gain, however, if the on-the-job wage growth of stayers does not serve as a good approximation for the wage growth movers would have received had they not moved. In order to correct for this bias, it is necessary to find a third group of individuals within the data who are associated with an earnings profile similar to *BG* in figure 4.2, which may be used to proxy the change in earnings that movers would have received had they not moved. One possibility, proposed by Mincer (1986), is to identify those individuals who stay in their jobs in the period over which the wage change equation is estimated, but who then switch jobs in the subsequent period. These "next period movers" may be associated with similar levels of unobservable characteristics to those workers who are observed as moving in the current period. Effectively, both "next period movers" and "current period movers" are considered as being members of the group of movers and so possess the characteristics associated with that group. In this case, the on-the-job wage growth that next period movers receive in the current period may be used as a way of approximating the growth in earnings that current period movers would have received had they not moved. Next period movers may therefore be seen as being on a profile similar to that of *BG* in figure 4.2. An estimate of the long run mobility wage gain may then be calculated by comparing the wage change of current period movers with next period movers.

Abbott and Beach (1994) adopt the dummy variable approach in order to estimate the mobility wage gain for a sample of Canadian women from the Labour Market Activity Survey. They consider a sample of individuals who held either one or two jobs during the period 1986-1987. From their sample, they identify several groups of individuals who are differentiated with respect to their mobility behaviour over the two year period. Firstly, there are 1986 movers, who experience a job change at some point during 1986. A second group of workers, defined as 1987 movers, remain on the same job throughout 1986, but then switch jobs during 1987. Finally, Abbott and Beach are able to identify the group of stayers, who are observed as remaining on the same job throughout the entire 1986-87 period. In order to calculate the mobility wage gain, Abbott and Beach estimate a single wage change equation for the 1986 period with the inclusion of dummy variables indicating the different types of mobility behaviour. By comparing the change in wages over the 1986 period for those who switch jobs in 1986 with the change in wages over the 1986 period for those who move in 1987, Abbott and Beach calculate the mobility wage gain to be around 8%. This estimate is believed to correct for selectivity bias since the groups of 1986 movers and 1987 movers are hypothesised to possess similar unobservable characteristics. The results obtained from the wage change equation also suggest that simply comparing current period movers with stayers would understate the mobility wage gain. Those who remain in the same job throughout the entire 1986-87 period are observed as having higher wage growth over the 1986 period than the group of 1987, or next period, movers. This result is consistent with Holmund's evidence concerning sample selection effects in that the wage growth of stayers tends to overstate the wage growth that movers would have received had they not moved.

4.4 Empirical methodology for estimating the gains from mobility

The search, matching and training approaches suggest that the gains arising from job mobility may occur either as a result of a shift in the earnings profile, or a change in the slope of the profile, or both. For the purposes of this study, the vertical shift in the earnings profile that occurs at the point of job change is referred to as the short run mobility wage gain (SRMWG). The total wage effect that includes both the shift in the profile and the change of slope is referred to as the long run mobility wage gain (LRMWG). Most existing empirical studies examining the wage effects associated with mobility offer an estimate of the LRMWG. In order to estimate this LRMWG, the existing literature highlights the need to employ a technique that addresses the issue of selectivity bias which arises when comparing two groups of individuals like movers and stayers. The first aim of the empirical analysis undertaken within this study is to derive an estimate of the LRMWG for UK employees using data from the British Household Panel Survey (BHPS). From this estimate of the LRMWG, an attempt is also made to identify the proportion of this gain that is due to a shift in the earnings profile (i.e. the SRMWG) and the proportion occurring as a result of a change in the gradient of the wage profile following mobility. Being able to perform such a decomposition is of interest because it enables an insight to be gained into whether the earnings profile shifts up or down following mobility and whether it becomes steeper or flatter. Answering these questions may contribute to an overall understanding of exactly how individuals gain in the long run by switching jobs. To estimate the LRMWG in the presence of possible sample selection effects, a version of the dummy variable approach similar to that of Abbott and Beach is used. An extension of this technique is then used in order to decompose the LRMWG into the two relevant components.

It is assumed that an individual enters the labour market at time *S* with a stock of general skills which remains constant throughout their working life. In figure 4.3 below, the individual is then observed at a later date, t_1, with earnings given by the point *B*. Fractionally after this date, the worker switches into an alternative job that pays a starting wage of *C*.[9] Once employed within this new job, earnings may grow as a result of specific human capital accumulation or as a result of additional information concerning actual productivity being revealed. The earnings profile over the period t_1 to t_2 for a current mover is then given by *BCD*. At time t_1, another individual is associated with earnings *B* who is observationally similar to the current mover but remains on the same job throughout the period t_1 to t_2. The earnings profile for the current stayer is given by the line *BF*. The profile of the mover is drawn steeper than the stayer reflecting the predictions of the matching and training approaches outlined in section 2. Those who remain on the job will have higher tenure at any point between t_1 and t_2 than the mover and so may receive less investment in specific human capital. With the stayer's higher tenure, it is also possible that the rate at which earnings grow as a result of the arrival of new information relating to actual productivity is lower.

[9] To keep the diagram simple, it is assumed that the starting wage in the new job exceeds the current wage i.e. the earnings profile shifts up following mobility.

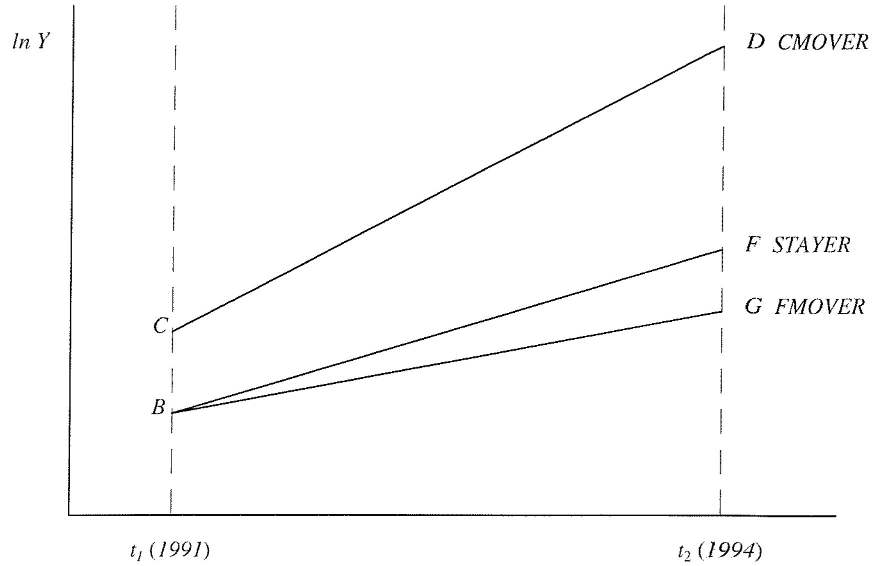

Figure 4.3 Estimating the long run mobility wage gain

The change in wages for the mover is given by the vertical distance between *B* and *D*, while for a stayer, the wage change is given by *BF*. The difference in the wage change of movers and stayers over the period t_1 to t_2 is then given by *FD*. As was discussed in the previous section, however, comparing the wage change of observationally similar movers and stayers may not provide an accurate estimate of the LRMWG. This is because stayers may be associated with unobservable characteristics that cause their on-the-job wage growth to be greater than the wage growth observationally similar movers would have received had they not moved. The technique used in this study to correct for this potential bias is similar to that used by Abbott and Beach. Some of the individuals who are observed as staying between t_1 and t_2 will go on to experience a job change at some point beyond t_2. These individuals are referred to as "future movers". It may be the case that future movers are more similar in terms of their unobservable characteristics to the group of current movers than current stayers. Without the same wage growth enhancing unobservable characteristics possessed by current stayers, a future mover may be associated with the profile *BG*.[10] The on-the-job wage growth of future movers in the period t_1 to t_2 may then be used as a way of approximating the change in earnings a current mover would have received had they not moved. An estimate of the LRMWG could then be derived by comparing the change in earnings of a current mover with

[10] When introducing future movers, the current stayer profile in figure 4.3, *BF*, should be viewed as being the profile associated with those who stay in both the current period and the future period. Whether the future mover profile, *BG*, lies above or below *BF* is an empirical issue and provides evidence for the direction of the selectivity bias.

that of a future mover. If both current movers and future movers are similar in terms of unobservable characteristics such as ability, then the difference in their earnings growth over the period t_1 to t_2 may be seen as occurring as a result of mobility and not as a result of differences in unobservable characteristics. The vertical distance *GD* may then provide an estimate of the LRMWG.

The estimate of the LRMWG will exceed the SRMWG (*GD* > *BC*) if the earnings profile becomes steeper following a job change. In order to derive an estimate of the SRMWG, it is necessary to find a way of filtering out the contribution made to the total wage gain arising from the movement onto a steeper earnings profile. If future movers may be used to approximate the wage change current movers would have received had they not moved, then it could be argued that the wage change over the period t_1 to t_2 of "past movers" may proxy the wage change current movers would have received had they already been employed in their new jobs at time t_1. From the set of individuals who are observed as remaining on the job between t_1 and t_2, there will be some who experienced a job change just before t_1. According to the matching and training hypotheses, these past movers will be associated with a relatively steep earnings profile since they are new to their current jobs and, therefore, have low tenure. The earnings profile of an individual who moved fractionally before t_1 may be given by the profile *BE* in figure 4.4.

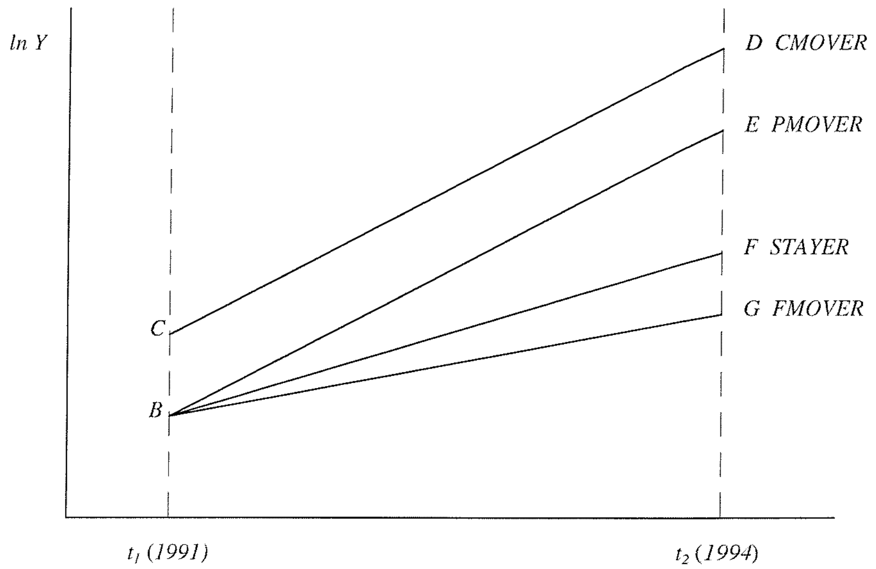

Figure 4.4 Estimating the short run mobility wage gain

Figure 4.4 shows the earnings profiles associated with current movers, past movers, and future movers. The stayers profile is different to that shown in figure 4.3 in that it now relates to individuals who not only remain in their jobs over the period t_1 to t_2, but who also stay on the same job in the "past" and "future" periods. These individuals may, therefore, be viewed as long term job stayers. As in figure 4.3, an estimate of the LRMWG may be derived by comparing the wage change of current movers with future movers. Some additional insight, however, into the wage effects associated with mobility may be gained by comparing the change in earnings of future movers with past movers. Neither of these groups of workers experience any mobility over the period t_1 to t_2 and both may be considered as possessing unobservable characteristics that are consistent with the overall sample of movers. In this case, the difference in wage change between these two types of workers, *GE*, may be seen as being due to the fact that past movers are associated with a steeper wage profile. The distance *GE* may then provide an estimate of the mobility wage gain arising from the movement onto a steeper earnings profile. When comparing current movers with future movers, the estimate of the LRMWG, *GD*, includes both the effect of a shift in the earnings profile and a change in slope. By subtracting from the LRMWG the estimate of the wage gain arising from the movement onto a steeper profile, *GE*, it is possible to derive an estimate of the vertical shift in the earnings profile associated with mobility (SRMWG). This estimate of the SRMWG, *ED*, will accurately estimate the actual SRMWG, *BC*, if the earnings profiles associated with past movers and current movers are parallel. If they are parallel, the main difference in the wage change of these two types of worker will be due to the vertical shift in the earnings profile received by current movers when they switch jobs.[11]

The empirical methodology described in this section, therefore, relies on being able to identify a worker's mobility behaviour over three periods. Although the wage change equation is only estimated for the current period, it is necessary to consider whether the individual experienced a job change in the previous period and in the subsequent period. By combining the information relating to mobility behaviour in each of the periods, an individual may be classified as either a mover or a stayer. A mover is defined as someone who experiences a job change in any of the three periods, while a stayer is defined as a worker who remains on the same job throughout all three periods. The groups of movers and stayers may possess different unobservable characteristics making it inappropriate to compare their

[11] It is unlikely that these two profiles will be parallel. At any point between t_1 and t_2, current movers will always have less tenure than past movers and so may be on a steeper profile. If past movers switched jobs fractionally before t_1 and current movers fractionally after t_1 the difference in these slopes may be small, but the more time that elapses between past movers and current movers switching jobs, the greater will be the difference in the slopes of their associated wage profiles.

wage changes in the current period in order to estimate the mobility wage gain. Instead, the wage change of those who switch jobs in the current period (current movers) may be compared to individuals who remain in their jobs in the current period but who experience mobility in either the previous or subsequent period (past or future movers). In particular, comparing current movers with future movers may provide an estimate of the LRMWG since these individuals may be associated with similar unobservable characteristics and so only differ in terms of their mobility decision within the current period. Additional insight into the wage gains arising from mobility may be obtained by comparing future movers with past movers. Essentially, the estimates of the mobility wage effects are calculated by comparing current, future, and past movers who are all assumed to belong to the overall group of movers. This technique provides a way of correcting for sample selection bias if the three different types of job mover are similar in terms of their unobservable characteristics.

4.5 Description of the BHPS data and statistical model

The methodology outlined in the previous section suggests that the wage effects associated with job mobility may be detectable by estimating a log wage change equation that includes a set of dummy variables capturing workers with different mobility behaviour. The data used to estimate this wage change equation is taken from the British Household Panel Survey, which is a longitudinal survey of a cohort of individuals interviewed annually from 1991 to 1999. The wage change equation is estimated over the years 1991-94, which is referred to as the current period. The methodology described previously requires not only being able to identify an individual's mobility behaviour within the current period, but also within the previous period and the subsequent period. The years 1994-97 are assumed to constitute the future period, while the years 1988-91 are referred to as the past period. The first step towards estimating the wage growth model, therefore, involves examining each individual's mobility behaviour within the current, past and future periods in order to determine which of the groups shown in figure 4.4 the individual is a member of.

4.5.1 Description of the mobility variables

The BHPS is a continuing longitudinal survey of individuals living in Great Britain. The first wave was undertaken in September 1991 with approximately 10,000 individuals being interviewed from 5,000 households. Annual follow ups have taken place in each year up to 1999, although only the data from the waves leading up to 1997 are referred to within this study. BHPS data contains a rich source of information relating to the jobs held by individuals during the 1990s. In particular, at the time of each interview, individuals provide information relating to the date at which their current job started. For those in employment at the time of the 1991 wave, data is available for the month and year in which the current job began. Using this information, it was possible to identify which individuals started their current job no more than three years before their date of interview in 1991.[12] Those who are observed as having started their current job at some point between 1988 and 1991 are considered as having experienced mobility within the 'past period'.

In 1994, individuals who are observed as being in employment are once again asked to register the date at which their current job started. Since the exact date of each interview is known, it is possible to determine whether the current job started at some point between the 1991 and 1994 interview dates. A dummy variable was then constructed to indicate whether the individual switched jobs between their 1991 and 1994 interviews. Individuals who are observed with a value of one for this variable are seen as experiencing a job change within the 'current period'. The definition of a current period mover, therefore, is only based on whether the worker is observed in a different job in 1994 compared to 1991. The number of moves made in this period and whether the job changes occur within the same firm or across firms is not explicitly considered.

The empirical methodology outlined in the previous section requires being able to identify job changes that occur in the period beyond that in which the wage change equation is estimated. This is achieved by analysing the start dates for the jobs held by workers at the time of the 1997 round of BHPS interviews. If the start date for the job held in this wave of the BHPS was between the 1994 and 1997 interview dates, the individual was recorded as having experienced mobility in the 'future period'. The sample of individuals obtained, therefore, is relatively restricted since it is required that individuals are in employment at the time of the 1991, 1994, and 1997 interviews. The wage change equation for the sample is estimated over the current period (1991-94), although information is available relating to mobility occurring in the past period (1988-91) and the future period (1994-97). Individuals within the sample may be considered in terms of two main groups, depending on whether or not they experienced any job changes over the entire 1988-97 period. The group who did experience mobility are then divided into four separate categories. Firstly, current movers (*CMOVER*) are identified as those who switch jobs during the current period. Past movers (*PMOVER*) are defined as being those who remain in the same job throughout the current period, but who switched jobs in the previous period. Those who do not change jobs in the current period, but who go on to experience mobility in the subsequent period are referred to

[12] Most of the interviews in 1991 took place in September, but in subsequent waves, the interviews occurred between September and April.

as future movers (*FMOVER*). Finally, there will be some multi-period movers (*PFMOVER*) who remain in the same job in the current period, but who experience job changes in both the past and future periods. Table 4.1 below summarises the mobility behaviour in each of the three periods for the four different types of job movers, along with the additional group of long term job stayers.

Variable name	*Description*	*1988-1991 (past period)*	*1991-1994 (current period)*	*1994-1997 (future period)*
STAYER	Stay in all periods	Stay	Stay	Stay
CMOVER	Current mover	Stay or Move	Move	Stay or Move
PMOVER	Past mover	Move	Stay	Stay
FMOVER	Future mover	Stay	Stay	Move
PFMOVER	Moves in both past and future	Move	Stay	Move

Table 4.1 The division of movers into four categories

The sample of individuals taken from the BHPS may therefore be considered in terms of two main groups. Firstly, there are those who experience no mobility over the entire 1988-97 period (*STAYER*). The second group of workers experience at least one job change during the nine year period. Some of these movers are observed as switching jobs in the current period (1991-94), while others remain in the same job in the current period but experience a job change in either the past period, or future period, or both. The empirical methodology used in this study suggests that to estimate the wage effects associated with mobility, it may be more appropriate to compare the wage change of current movers in the 1991-94 period with the wage changes of past movers and future movers in the same three year period. All of these individuals are assumed to belong to the overall group of movers and so may be relatively similar in terms of unobservable characteristics such as ability. Using the wage change of long term stayers (*STAYER*) over the 1991-94 period to approximate the wage change that current movers would have received had they not moved may lead to an inaccurate estimate of the mobility wage gain being obtained. This is because current movers and stayers are assumed to be members of different groups of workers who differ with respect to various wage enhancing unobservable characteristics.

4.5.2 Equation to be estimated

The version of the wage change equation estimated using the BHPS data is similar that of Keith and McWilliams (1997). The change in earnings between 1991 and 1994 is regressed on a set of control variables and a number of dummy variables representing the five types of worker described in table 4.1. The wage change equation to be estimated may be written in the following form:

$$\begin{aligned}\Delta \ln W_i &= \delta \ln W_{i,1991} + \beta_2 \Delta X_i + \beta_3 CMOVER_i + \beta_4 PMOVER_i \\ &+ \beta_5 FMOVER_i + \beta_6 PFMOVER_i + \varepsilon_i^* \end{aligned} \qquad (4.1)$$

where $\Delta \ln W_i$ is the change in deflated log gross monthly pay between 1991 and 1994
$ln W_{i,1991}$ is deflated log gross monthly pay in 1991
ΔX_i is the change in the values of a set of explanatory variables between 1991 and 1994
$CMOVER_i$ equals one if the individual changed jobs at some point between 1991 and 1994
$PMOVER_i$ equals one if the worker is a past mover
$FMOVER_i$ equals one if the worker is a future mover
$PFMOVER_i$ equals one if the worker is a multi period mover
$STAYER_i$ equals one if the worker is a stayer (excluded case)
ε_i^* is a random error term and δ, β_2 to β_6 are coefficients to be estimated

As shown by Holmlund (1984) and Keith and McWilliams, the inclusion of the initial wage allows the coefficients associated with the explanatory variables to vary between the two wage level equations that form the wage change equation. In moving from 1991 to 1994, each individual will accumulate a number of years of additional experience within the labour market. This change in experience, valued according to the return per year of experience in 1994, could be entered as an explanatory variable in the wage change equation. It is possible, however, that the return per year of experience within the 1994 wage level equation is different from that associated with the 1991 wage level equation. The inclusion of the initial (1991) wage detects any difference in the coefficients of the explanatory variables in 1991 (β_1) with those in 1994 (β_2). A negative coefficient estimate for δ would imply that that the coefficients associated with the explanatory variables in 1994 are lower than those in 1991. If the coefficients relating to variables such as years of experience are observed to be declining, the inclusion of initial earnings in the wage change equation will capture the concave nature of the experience-earnings profile when viewed across the whole life cycle.[13] When including initial earnings, however, there is the possibility of obtaining biased coefficient estimates in

[13] In the empirical approach described in section 4 and depicted in figure 4.4, the log wage profile is seen as being linear. Over a short interval, such as three years, the profile could be approximated as a linear function, although over the full working life, the profile may be of a concave nature.

the wage change equation due to the potential correlation between the initial wage and the composite error term.[14]

Although many existing studies include the change in years of experience within the wage change equation, this variable is not included in the estimation of (4.1) using the BHPS. Instead, a dummy variable was constructed indicating whether each individual within the sample worked continuously throughout the 1991-94 period, or experienced any spells of unemployment. The theoretical approaches discussed in section 2 generally relate to job changes that occur voluntarily. Workers who voluntarily switch jobs may be less likely to experience any spells of frictional unemployment over the period in which the wage change equation is estimated. For the sample of individuals working continuously over the 1991-94 period, the only discontinuity in the wage profiles depicted in figure 4.4 is associated with the vertical shift experienced by the group of current movers at the point of job change. In order to estimate the wage gains associated with mobility as illustrated in the previous diagrams, equation (4.1) is initially estimated for those who remain in continuous employment from 1991 to 1994. As an extension, the equation is then estimated allowing for the possibility that some individuals experience a spell of unemployment when moving from one job to another. Since any workers observed with unemployment will be employed in a different job in 1994 to the one held in 1991, the sample of current period movers is separated into those who switch jobs with no unemployment over the three year period and those who switch jobs but experience intervening unemployment.

The existence of an unemployment spell is likely to have several effects on the change in earnings over the period 1991-94 for the group of current movers. One possibility is that it exerts an additional effect on the shift in the earnings profile that arises when the new job commences. It could be the case that the earnings profile shifts down as workers who are laid off are willing to accept a low starting wage in the new job in order to minimise the time spent in unemployment. Alternatively, during the unemployment spell, an individual may search more intensely allowing them to identify a new job offering a higher starting wage. In this case, the earnings profile would shift upwards relative to its position in the previous job. Workers who switch jobs with intervening unemployment may also be expected to suffer a wage penalty relative to those who switch jobs instantaneously since no on-the-job wage growth is possible throughout the duration of the unemployment spell. Even if they do

[14] A more detailed discussion of the wage change model and the potential estimation concerns is presented in appendix C.

eventually find a job similar to that of instantaneous movers, their subsequent earnings in the new job will always be lower since several periods of on-the-job wage growth would have been lost relative to those who switch jobs without experiencing unemployment. With the data available, it would be difficult to identify the exact wage effects arising from mobility involving a spell of unemployment. Simply segregating the movers into those who switch jobs with and without intervening unemployment, however, may provide some insight into the average wage effects of these two forms of mobility. Those who switch jobs without experiencing unemployment may be seen as voluntary job movers, while those who do experience a spell of unemployment between jobs could be viewed as involuntary movers. Evidence from existing studies generally finds that workers who quit their jobs receive positive gains while those who are laid off are associated with negative gains (Bartel and Borjas 1981; Keith and McWilliams 1997).

In addition to the mobility variables, equation (4.1) also contains some further explanatory variables. These variables relate to changes in marital status, educational attainment, and usual hours worked per week between 1991 and 1994.[15] All of these variables are obtained at the date at which individuals within the sample were interviewed. At the time of interview, individuals are also asked to provide information relating to their earnings within the job currently held. The dependent variable used in (4.1) is the real change in log usual gross monthly pay between the 1991 and 1994 interview dates.[16] For the reasons outlined previously, log gross monthly pay in 1991 is also included among the set of explanatory variables.

4.5.3 Summary statistics

From the BHPS, a final sample of 1050 men and 623 women was obtained. All of these individuals were observed as being in employment at the time of the 1991, 1994, and 1997 waves of BHPS.[17] Within this sample, 965 (or 92%) of the men and 588 (or 94%) of the women were observed as experiencing no unemployment during the 1991-94 period in which

[15] For each of the 1991 waves, a set of six dummy variables was constructed indicating the highest academic qualification obtained. An individual's educational attainment changes if they move up at least one category on the six level classification. Appendix C provides the details of this classification.
[16] Given the exact date of interview, the earnings data for 1991 and 1994 is deflated using the retail price index with January 1991 as the base month.
[17] The sample was restricted to only include full time employees at the time of 1991 and 1994. Since the 1997 wave is only used to determine whether individuals were still in employment, and no earnings data is used from this wave, the restrictions of full time employment and not being in self employment are not applied.

the wage change equation was estimated.[18] The figures presented in table 4.2 below show that for the sample of males who worked continuously, 34% of individuals experienced a job change at some point between 1991 and 1994. A further 30% of men were observed as not only staying in the current period, but also in the previous and subsequent periods (*STAYER*). The percentage of male employees identified as being past movers and future movers were 16% and 9% respectively. The remaining 10% of men stayed in the current period, but moved in both the previous and subsequent periods (*PFMOVER*). The corresponding figures associated with female current movers, stayers, past movers and future movers are found to be 40%, 21%, 21% and 7% respectively.

Sample	*Men*			*Women*		
	N	*WGROWTH*	*PAY91*	N	*WGROWTH*	*PAY91*
CMOVER	332	0.150 (0.349)	7.108 (0.476)	233	0.166 (0.272)	6.751 (0.450)
PMOVER	159	0.139 (0.329)	7.057 (0.525)	122	0.114 (0.212)	6.740 (0.495)
FMOVER	90	0.046 (0.174)	7.124 (0.387)	40	0.067 (0.218)	6.789 (0.431)
PFMOVER	95	0.108 (0.234)	7.035 (0.550)	67	0.109 (0.187)	6.736 (0.483)
STAYER	289	0.078 (0.260)	7.060 (0.439)	126	0.056 (0.269)	6.680 (0.505)

Table 4.2 Means and standard deviations for the change in log gross monthly pay between 1991 and 1994 (*WGROWTH*), and log gross monthly pay in 1994 (*PAY91*)

The figures shown in table 4.2 offer some preliminary evidence relating to the effect that mobility has on earnings growth. It may be seen that for both males and females, current movers are associated with the greatest log wage change over the 1991-94 period. An important point to note is that for men, the wage change of future movers over the 1991-94 period (*FMOVER*) is less than that of long term job stayers (*STAYER*). This would imply that an estimate of the long run mobility wage gain based on a comparison of current movers with stayers would be less than that based on a comparison with future movers. For women, however, comparing current movers with stayers would overstate the total wage gain since future movers are observed as having higher wage growth than stayers. The observation of lower wage growth associated with male future movers is consistent with the matching approach in the sense that individuals who are on the verge of switching jobs are the ones

[18] Individuals who experienced time out of employment for other reasons, e.g. maternity leave and full time education, are excluded from the initial samples of 1050 men and 623 women.

most likely to currently be employed in relatively poor matches. Following a job change, these individuals may move onto a steeper wage profile. It may be seen in table 4.2 that for both males and females, those who recently switched jobs (*PMOVER*) are observed to have higher wage growth than future movers. If both past movers and future movers are similar in terms of characteristics such as unobservable ability, the difference in their wage growths over the 1991-94 period may be seen as being due to the movement onto a steeper wage profile following a job change. Overall, the figures in table 4.2 provide some evidence for the positioning of the earnings profiles associated with the different types of workers depicted in figure 4.4.

4.6 Results

Some estimates of the short run and long run mobility wage gains were derived by estimating equation (4.1) separately for the samples of BHPS males and females. The dependent variable is the change in log gross monthly earnings between 1991 and 1994. This wage change is regressed on a set of explanatory variables and four dummy variables representing the four different categories of job mover. The fifth type of worker, long term stayers (*STAYER*), represents the excluded case when estimating the wage change equation. The results obtained from estimating such a wage change equation for males and females are presented in table 4.3 below. Columns (1) and (3) report the results obtained for men and women when the sample is restricted to only include those who work continuously between 1991 and 1994. In columns (2) and (4), the sample also includes those who experienced a spell of unemployment between the jobs held in 1991 and 1994. Since those who experience unemployment would have changed jobs, the current mover category is segregated into those who switched jobs with no unemployment, *CMOVER(no u/p)*, and those who switched jobs with a spell of intervening unemployment, *CMOVER(u/p)*.

It may be seen in all of the columns in table 4.3 that the coefficient associated with initial log earnings (*PAY91*) is found to be negative and statistically significant. In terms of the statistical model outlined in section 5.2, this implies that the coefficients attached to the explanatory variables included within the wage level equations are greater in the 1991 equation than in the 1994 equation. Any changes in the explanatory variables between these two dates, such as becoming married, contributes to the total wage change in accordance with the value of being married in 1994. The value of being married in 1994, however, may be lower than that in 1991. The results shown in table 4.3 suggest that, in general, changes in the explanatory variables have no significant effects on the change in earnings between 1991 and 1994. Higher educational attainment ($\Delta EDUC$) has no significant effect on the change in log wages, while an increase in the number of hours (Δ*HOURS*) worked only significantly raises the wage growth of females. Surprisingly, for men, becoming married (*SINGLE-MARRIED*), or becoming single (*MARRIED-SINGLE*) both negatively affect wage growth relative to those whose status does not change, although the effect is only significant for the latter. The opposite, however, is found for women, where any change in marital status positively affects earnings, although both changes are insignificant at the 10% level.

Variable	**Male coefficients and *t*-ratios**		**Female coefficients and *t*-ratios**	
	(1)	(2)	(3)	(4)
PAY91	-0.240 (7.502)	-0.265 (8.876)	-0.120 (4.761)	-0.149 (5.581)
Δ HOURS	0.001 (0.527)	0.002 (1.253)	0.008 (2.524)	0.008 (2.470)
Δ EDUC	-0.002 (0.060)	0.002 (0.055)	-0.014 (0.346)	0.001 (0.032)
SINGLE-MARRIED	-0.026 (0.865)	-0.021 (0.702)	0.061 (1.710)	0.053 (1.486)
MARRIED-SINGLE	-0.112 (2.024)	-0.104 (1.956)	0.074 (1.225)	0.058 (0.999)
CMOVER	0.081 (3.526)	-	0.115 (3.910)	-
CMOVER(u/p)	-	-0.134 (3.062)	-	0.030 (0.373)
CMOVER(no u/p)	-	0.082 (3.567)	-	0.117 (3.953)
PMOVER	0.057 (1.986)	0.055 (1.938)	0.063 (2.034)	0.065 (2.105)
FMOVER	-0.022 (0.954)	-0.020 (0.826)	0.026 (0.676)	0.029 (0.759)
PFMOVER	0.020 (0.762)	0.014 (0.548)	0.0622 (1.873)	0.063 (1.871)
constant	1.783 (7.730)	1.958 (9.110)	0.852 (4.871)	1.044 (5.670)
R-squared	0.1669	0.01913	0.1145	0.1234
F	9.48	11.52	5.66	6.16
N	965	1050	588	623

Table 4.3 Estimation of equation (4.1) where the dependent variable is the log wage change 1991-94

The coefficients of particular interest are those associated with the dummy variables capturing the different types of job movers. Those who remained on the same job throughout the entire 1988-97 period (*STAYER*) represent the excluded case so the estimated coefficients for the dummy variables capture the difference in the log wage change between the different types of mover and the long term stayers. For the sample of 965 males who worked continuously, column 1 of table 4.3 suggests that current movers (*CMOVER*) receive the highest change in earnings between 1991-94 out of the five categories of individuals. The wage change of these current movers is found to be significantly greater than long term stayers. Comparing the wage change of current movers and stayers within the current period could be used as a way of estimating the long run mobility wage gain. As has been argued previously, however, this estimate of the LRMWG may be inaccurate if current movers and stayers form two different groups of individuals who differ with respect to their unobservable characteristics. In the presence of such unobservable differences, the on-the-job wage growth of stayers within the current period may not be a good approximation of the wage growth current movers would have received had they also remained on the same job. The technique used in this study to estimate the LRMWG is to compare the wage change of current movers with those who are observed as staying in the current period but who move in the subsequent period i.e. future movers (*FMOVER*). This comparison may provide an estimate of the LRMWG which corrects for selection bias if both current and future movers are assumed to belong to the overall group of movers and so possess similar unobservable characteristics. The difference in the wage changes between these two types of mover may then be seen as being a consequence of mobility and not due to differences in unobservables.

One of the most important features of the results shown in table 4.3, column 1 is that within the current period, the wage change of male future movers (*FMOVER*) is lower than that of stayers, although the difference is found to be insignificant. This is consistent with the evidence concerning the direction of the sample selection bias found in the studies reviewed in section 3. If the wage change of future movers is interpreted as a proxy for the wage change current movers would have received had they not moved, it would appear that stayers do better by remaining on the job than movers would do if they also stayed. The estimate of the LRMWG may then be derived from the difference in the coefficients associated with current movers and future movers (β_3 minus β_5 in equation (4.1)). Male current movers receive, on average, 0.081 higher log wage change than stayers, while the log wage change of future movers is 0.022 less than stayers. The difference in log wage change between current movers and future movers is then 0.103 which gives a LRMWG estimate for men of 10.8%.[19]

The estimate of the LRMWG will include both the gains arising from a shift in the earnings profile and from a change in the slope of the profile. In order to gain additional insight into the way in which individuals gain by switching jobs, it is necessary to be able to identify the separate contributions that shifts and changes in the slope of the earnings profile make to the LRMWG. The method used for attempting such a decomposition involves comparing the wage change in the current period of future movers with past movers. Neither of these individuals experience mobility within the current period so any difference in their wage change will not be due to a shift in the earnings profile that occurs at the point of job change.

[19] The antilog of 0.103 minus one is 0.108.

If both of these individuals are assumed to be members of the overall group of movers, they may be associated with similar characteristics such as unobservable ability. With this assumption, the difference in their wage changes will not be a result of one category of individuals being associated with higher ability. The difference in their wage changes over the 1991-94 period may therefore be interpreted as capturing the idea that those who have recently switched jobs have moved onto an earnings profile that has a different gradient to those who are on the verge of a job change. The wage changes of future movers and past movers are viewed as representing the slope of the earnings profile before and after the move respectively.

The results in column 1 of table 4.3 imply that for males, past movers receive higher wage change over the 1991-94 period than future movers. By undertaking the relevant *F*-test, the difference in the wage change between these two types of mover was found to be significant. It would appear, therefore, that individuals who are new to a job are associated with a steeper earnings profile than those who are about to switch into a new job. This provides some empirical support for the versions of the matching and training hypotheses described in section 2. New recruits will always have lower tenure throughout the 1991-94 period than future movers and so may receive greater investment in specific human capital. Alternatively, those new to a job may see their earnings rise at a faster rate as a result of larger wage adjustments taking place when new information arrives concerning actual productivity on the job. The comparison of future movers with past movers enables the contribution made to the LRMWG arising from the movement onto a steeper wage profile to be identified. For males, the difference in the log wage changes of future movers and past movers is, on average, 0.079. The total difference in the log wage change between current movers and future movers (which is used to calculate the LRMWG) is 0.103. As a proportion of the LRMWG, the wage gain arising from the movement onto a steeper earnings profile may then be calculated as 76.7%. The remaining 23.3%, which may also be seen from the difference between current movers and past movers, may then be considered as an estimate of the vertical shift in the earnings profile that follows mobility, or the short run mobility wage gain (SRMWG).[20] As was discussed in section 4, the accuracy of these estimates depends on how similar the slopes of the wage profiles of current movers and past movers are over the 1991-94 period. If the profile associated with current movers is steeper, the estimate of the vertical shift in the

[20] If the earnings profiles of current movers and past movers are close to being parallel, the only difference in the wage change between these individuals is due to the vertical shift received by the current movers when they switch jobs.

profile that occurs at the point of job change will be overstated while the gain arising from a change of slope will be understated (see figure 4.4).[21]

The third column of table 4.3 reports the results obtained from estimating equation (4.1) for the sample of women who worked continuously throughout the 1991-94 period. It may be seen that women who experience a job change during the three year period receive an average wage gain of 12.2% relative to stayers. In contrast to the male results, however, comparing the wage change of current movers with stayers overstates the size of the long run mobility wage gain. This is because in the female equation, future movers are associated with higher wage growth over the 1991-94 period than stayers, although the difference is statistically insignificant. This finding would appear to suggest that the selectivity bias runs in the opposite direction to that which would be expected. The positive coefficient associated with *FMOVER* implies that current movers would have received higher wage growth over the 1991-94 period had they remained in their jobs than those who are observed as actually staying in their jobs. In order to calculate the LRMWG it is then necessary to compare the change in log earnings in the 1991-94 of current movers with future movers. By performing this calculation, an estimate of 9.3% is obtained for the LRMWG. Following this estimate, it is possible to identify the part of the total wage gain that is attributable to a shift in the earnings profile and the part arising from a change in the slope of the profile. The results shown in column 3 of table 4.3 imply that women who switched jobs in the previous period are associated with higher wage growth in the current period than those who experience mobility in the future period. As in the interpretation of the male coefficients, the difference in the log wage changes of past movers and future movers is seen as capturing the effect that mobility has on the slope of the earnings profile. From the results obtained, women who recently switched jobs receive, on average, a log wage gain of 0.037 as a result of moving into a job with a steeper earnings profile. This is 41.6% of the total log wage gain (0.089), leaving the remaining 58.4% to form an estimate of the vertical shift in the earnings profile that occurs at the point of job change (SRMWG). Table 4.4 below summarises the estimates

[21] There may also be another, more serious inaccuracy in the estimates. In figure 4.4 it was assumed that current movers switched jobs fractionally after the initial period e.g. 1991. It is possible that a worker could remain on the initial job for a while after 1991, receive a pay cut when they switch jobs and then move into a job with an earnings profile steeper than that of past movers. By 1994 the current mover may still be observed with higher earnings than that of a past mover. The technique used to decompose the LRMWG, however, would estimate the vertical shift to be positive since it assumes that the profile of past movers is parallel to that of current movers. Too little of the LRMWG would then be attributed to a change in slope, leaving a positive remainder attributed to the SRMWG. The technique used would only yield a negative estimate of the SRMWG if current movers had lower earnings in 1994 than past movers.

of the LRMWG and SRMWG obtained from the samples of males and females who work continuously between 1991 and 1994.

	Men	**Women**
Estimate of long run mobility wage gain (LRMWG)	10.8%	9.3%
% of LRMWG attributable to a change in slope of the earnings profile	77%	42%
% of LRMWG attributable to a shift in the earnings profile (SRMWG)	23%	58%

Table 4.4 Estimates of the long run and short run mobility gains

The estimates of the mobility wage gains displayed in table 4.4 are likely to be influenced by the mean age and tenure of the movers within the samples of men and women who remain continuously employed between 1991 and 1994. The three approaches to mobility described in section 2 suggest that the magnitude of the long run mobility wage gain varies with respect to age and tenure. For example, in the search approach, older and more experienced workers are less likely to identify an alternative job offering a substantially greater wage than that received in their current job. In the matching and training approaches, workers with a high level of tenure will be associated with a relatively flat earnings profile, generating the potential for large wage gains to be received by switching into a job with a steeper profile. For the sample of 965 men who worked continuously over the three year period, the mean age and tenure in 1991 of the 332 workers who went on to switch jobs during the subsequent three years is 32.4 and 3.7 years respectively. These figures compare to means of 35.5 and 5.5 years for the entire sample, so it would appear that relative to the full sample, the group of current period movers are not substantially different with respect to these two characteristics. For women, the mean age and tenure of the current period movers is 33.0 and 3.0 years respectively, which compares to figures of 35.3 and 4.0 for the full sample of 588 individuals.[22]

Column 2 of table 4.3 presents the results obtained when the male wage change equation is estimated with the inclusion of individuals who experienced a spell of unemployment during

[22] The mean age and tenure in 1991 for each of the different groups of individuals is presented in table 4.7 of appendix C. For both males and females, stayers are associated with the highest values for mean age and tenure.

the 1991-94 period. Since these individuals would be employed in a different job in 1994 compared to 1991, the effect of unemployment is incorporated by dividing the sample of current movers into those who switched jobs with and without intervening unemployment. The coefficient associated with *CMOVER(u/p)* implies that workers who change jobs with unemployment receive 12.5% lower wage growth over the 1991-94 period than long term job stayers. As in column 1, those who smoothly switch from one job to another, *CMOVER(no u/p)* earn around 8% more than stayers. These results would suggest that the costs of being laid off are relatively large, assuming that those who switch jobs with intervening unemployment are changing jobs involuntarily. Over the three year period, involuntary movers would appear to receive lower wage growth than what they would have received had they not moved (given by the *FMOVER* coefficient), while those who appear to voluntarily switch jobs do considerably better. This result would appear to be consistent with the findings of other studies. For women, however, it is found that the cost of job loss over the three year period is almost zero. In column 4 of table 4.3, women who switch jobs with intervening unemployment are associated with the same change in earnings as future movers. In this case, any costs associated with job loss are exactly offset by the gains from (involuntary) mobility when measured over the three year period.

In outlining the statistical model in section 5.2, it was discussed how the estimated coefficients within the wage change equation may be biased due to the potential correlation between the error term and initial earnings. The composite error term in (4.1) will include the error term from the 1991 wage level equation. It is therefore likely that when including 1991 earnings as an explanatory variable within the 1991-94 wage change equation, it will be correlated with the composite error term. In order to obtain unbiased coefficient estimates for the wage change equation, it is necessary to re-estimate the model by instrumental variables, where predicted values of 1991 pay are used in place of actual values. Predicted values of initial earnings were obtained by estimating a wage level equation where 1991 earnings was regressed on a set of explanatory variables. The instruments used within this equation relate to tenure in the job held in 1991, age, region of residence, and regional unemployment.[23] Full details of this estimation and the results obtained are presented in table 4.6 of appendix C. The results from re-estimating (4.1) with the inclusion of predicted values for initial earnings, *PAY91(predicted)*, in place of the actual values are shown in table 4.5 below.

[23] Monthly regional unemployment data was obtained from NOMIS and matched to each individual according to their region of residence and date of interview in the 1991 wave of the BHPS.

Variable	Male coefficients and *t*-ratios		Female coefficients and *t*-ratios	
	(1)	(2)	(3)	(4)
PAY91*(predicted)*	-0.191 (5.040)	-0.219 (5.872)	0.027 (0.459)	0.005 (0.089)
Δ HOURS	0.002 (0.907)	0.003 (1.647)	0.010 (2.837)	0.010 (2.858)
Δ EDUC	-0.019 (0.471)	-0.017 (0.444)	0.020 (0.465)	0.043 (0.862)
SINGLE-MARRIED	-0.048 (1.461)	-0.046 (1.421)	0.060 (1.648)	0.052 (1.429)
MARRIED-SINGLE	-0.132 (2.145)	-0.127 (2.126)	0.081 (1.340)	0.057 (0.979)
CMOVER	0.068 (2.759)	-	0.104 (3.740)	-
CMOVER(u/p)	-	-0.103 (2.118)	-	0.058 (0.659)
CMOVER(no u/p)	-	0.067 (2.722)	-	0.105 (3.784)
PMOVER	0.056 (1.822)	0.053 (1.765)	0.054 (1.828)	0.057 (1.910)
FMOVER	-0.033 (1.363)	-0.032 (1.305)	0.011 (0.275)	0.013 (0.329)
PFMOVER	0.028 (1.010)	0.023 (0.840)	0.054 (1.668)	0.053 (1.628)
constant	1.442 (5.335)	1.638 (6.167)	-0.131 (0.326)	0.013 (0.032)
R-squared	0.0584	0.0720	0.0655	0.0555
F	5.00	6.03	3.13	2.86
N	965	1050	588	623

Table 4.5 Estimation of (4.1) with predicted values of initial earnings

It may be seen that the estimated coefficients reported in table 4.5 are similar to those of table 4.3. For men, the estimate of the LRMWG is calculated to be 10.6% of which 88% is attributed to the movement onto a steeper wage profile following a job change. The LRMWG for women is found to be 9.7% of which 46% is due to recent movers being associated with a steeper wage profile.

4.7 Conclusion

The switching from one job to another would appear to be a common activity within the labour market since in the sample of BHPS individuals used in this study, around 35-40% experience mobility during the years 1991-94. If individuals do experience a number of job changes within their working lives, the wage effects associated with such mobility is likely to be an important determinant of lifetime earnings. It then becomes an important empirical issue to attempt to estimate the magnitude of these mobility gains and the form that these gains take. Theory suggests that the mobility wage gain will be positive in the long run since individuals only switch jobs if they gain from doing so in terms of lifetime earnings. This long run gain, however, may arise from a shift in the earnings profile at the instant the job change occurs, or from a change in the rate of on-the-job wage growth when moving from one job to another, or both. Most existing estimates of the mobility wage gain are long run estimates in that they include both the wage effects associated with a shift and a change in the slope of the earnings profile. The main aim of this study has been to develop an empirical approach that allows not only the long run gain to be estimated, but also an attempt to be made at breaking this gain down into its constituent parts. For a sample of UK individuals taken from the BHPS, it was found that the total mobility wage gain arising over a three year period was 10.8% for males and 9.3% for females. For men, approximately three-quarters of this gain is interpreted as a result of individuals moving into a job with a steeper earnings profile and the remaining one-quarter being attributed to a positive shift in the profile at the point of job change. In the case of women, an upward shift in the earnings profile and the movement onto a steeper profile both account for around 50% of the total mobility wage gain over the three year period.

As in many existing studies of mobility, the empirical analysis undertaken highlights the existence of selectivity bias, which should be controlled for when deriving estimates of the mobility wage gains. To estimate the long run mobility wage gain, it is necessary to find an approximation for the wage growth movers would have received had they not moved. Using the on-the-job wage growth of those individuals who are observed within the data as staying in their jobs over the relevant period may not be a suitable approximation. This is because many of these individuals may remain within their jobs for long periods of time and may be considered as a different group of individuals who possess different unobservable characteristics. The methodology used in this study suggests that the individuals who are observed as staying in their jobs over the current period should be separated into those who experience mobility either in the previous period or the subsequent period, and those who experience no mobility over a long period of time. Individuals who experience mobility in either the past, current or future periods are considered as belonging to a group of overall movers, while those who stay in all periods form another group. These groups of individuals may differ in terms of their unobservable characteristics which means that when comparing the wage change of movers with long term stayers, it is not possible to detect how much of the difference is due to mobility and how much is due to unobservable differences between the individuals. If past, current and future movers, however, are similar in terms of such unobservables, then comparing the wage changes of these individuals may enable the wage effects associated with mobility to be detected. In particular, the difference in the wage changes of current movers and future movers may estimate the long run mobility wage gain if the on-the-job wage growth of future movers approximates the earnings growth current movers would have received had they not moved. The results obtained for men suggested that future movers receive lower on-the-job wage growth than long term stayers. For women, however, evidence was found for the existence of selectivity effects running in the opposite direction, with future movers being associated with higher wage growth than stayers. In both the male and female equations, however, the difference in wage growth of future movers and stayers was insignificant, suggesting that overall, failure to account for selectivity bias has little effect on the estimates of the mobility wage gains.

One of the main limitations of the study is that it does not adequately consider the case of mobility wage effects that differ according to the type of job change experienced. In the most basic regressions, an individual is defined as being mobile if they are employed in a different job at one point in time compared to an earlier date. No distinction is therefore made between job changes that occur within the same firm or across firms. As a way of attempting to distinguish between voluntary and involuntary separations, the sample of current movers was divided into those who experienced no unemployment between jobs and those who did experience intervening unemployment. It was found that there exists relatively large costs associated with job loss in that those who have a spell of unemployment between jobs are associated with lower wage growth over a three year period than those who continue in the same job throughout. This result is consistent with other studies which use superior data to analyse the wage effects of different types of job change.

Chapter 5 Conclusions

The three main chapters within the thesis form an empirical analysis of some of the factors that are important in determining an individual's earnings at various points within their working life. Since its formulation in the 1960s, the theory of human capital accumulation has maintained its status as the dominant model of earnings determination. Much of the research undertaken by labour economists incorporates elements of the human capital approach within the chosen empirical methodology. In its simplest form, human capital theory depicts the acquisition of productivity enhancing skills as a form of investment. Individuals are willing to sacrifice time and earnings in the present in order to develop such skills, which will increase their future productivity and, therefore, earnings in the labour market. The incentive to invest in human capital is anticipated to be strongest early in the life cycle since this allows a greater number of future periods for the returns on such investments to be received. In the very early stages of the life cycle, the incentive to invest is sufficiently strong that individuals elect to devote all of their available time to human capital acquisition. This part of the life cycle relates to the period of full time schooling. The second and third chapters of the thesis examine the effect that schooling has on subsequent labour market earnings. In particular, chapter 2 investigates the case where females enter the labour market earlier and with lower starting salaries than males as a consequence of investing in a lower quantity of schooling. The third chapter then explores the hypothesis that individuals with the same quantity of schooling may be observed with different levels of earnings as a result of differences in the quality of the education received.

Within the UK, there are a number of studies examining the earnings differential that exists between male and female workers. This literature generally concentrates on identifying the extent to which discrimination by gender exists within the labour market. In order to identify the discriminatory component of the observed wage gap, it is necessary to calculate the part of the wage differential that arises from males and females possessing different quantities of human capital. A smaller number of studies actually focus on the reasons why males and females may be observed with differing levels of human capital. Theoretical models predict that females have a lower incentive to invest in human capital than similarly able males, since the anticipation of career breaks lowers the number of periods over which the returns on such investments may be collected. The model outlined in chapter 2 considers investments made over the life cycle and shows that the expectation of a future career break reduces the number of years that women devote to full time education. Women who enter the labour market with a lower quantity of formal schooling are then predicted to receive lower salaries at the point of entry relative to those anticipating continuous participation. If there is no direct discrimination in the sense that the rate of return to schooling is equal for continuous and intermittent participants, differences in the starting salaries between these groups may be related to differences in the incentive to invest in full time education. The statistical analysis undertaken in chapter 2, therefore, provides a way of directly testing the idea that female workers are associated with a weaker incentive to invest in human capital, even in the early years of their lives.

Using data from the National Child Development Study, chapter 2 found some evidence to support the hypothesis that women who went on to experience interruptions to their careers by the age of 33 entered the labour market at a significantly earlier date than similarly able males and females who experienced no such breaks. With intermittent participants entering the labour market earlier and with a lower stock of human capital, it would also be expected that these individuals would be associated with lower starting salaries. After controlling for other factors that may determine starting salaries, ordinary least squares estimation revealed that women experiencing any type of future career break received 10% lower initial earnings than males. Further estimations for the sample of NCDS females showed that each year of non participation reduced starting salaries by approximately 1%. In recognition of the possible endogeneity between starting salaries and future career breaks, and also between entry dates and future non participation, the equations for the sample of females were re-estimated by two stage least squares. As in the OLS estimates, each year of non participation lowered initial labour market earnings by 1%, although the effect was found to be statistically insignificant. The negative effect of non participation on entry dates, however, was maintained within the 2SLS approach. Overall, therefore, some support was found for the hypothesis that women anticipating future spells of non participation elect to invest in less formal education, but the effect that this has on earnings at the point of entry was less conclusive.

In addition to examining the effect that anticipated spells of non participation have on the incentive to invest in full time education, chapter 2 also provides evidence for the quantity of schooling being an important determinant of earnings. Individuals planning to work continuously were found to enter the labour market having devoted more time to schooling and receive higher earnings in their first job. This result is consistent with the findings of extensive research undertaken in many countries that estimate the rate of return to an additional year of schooling as being positive. It is often argued, however, that in addition to the quantity of schooling affecting earnings, the quality of education received plays a role in determining subsequent labour market earnings. Some studies that have been undertaken using US data have found that individuals receiving higher quality schooling, measured by the pupil-teacher ratio, expenditure per pupil and average teacher salary, are associated with higher earnings later in life. Evidence from the UK, however, has generally found that these conventional measures of quality are insignificant determinants of earnings. Chapter 3 also attempted to test the hypothesis that the quality of education influences earnings using data from the NCDS, but employed a different empirical methodology to that used in previous UK studies. A two stage approach was followed where in the first stage, an estimate of the return to schooling was obtained for each of the LEAs in England and Wales in which the NCDS cohort could have received their secondary schooling. The results obtained from this first equation suggested that for 33 year old males, the rate of return to an additional year of schooling ranged from 6% to 18%. The mean rate of return across the LEAs was found to be approximately 10%, which is slightly higher than the estimates obtained by Dearden (1999b) using the NCDS. In the second stage of the statistical analysis, the LEA-specific rates of return were regressed on variables relating to the average quality of schooling within each of the LEAs. The mean pupil-teacher ratio, expenditure per pupil, and teacher salary, however, were found to exert no significant effects on the estimated rates of return to schooling. This result of quality not exerting an indirect effect on earnings through the rate of return to schooling reinforces the findings of existing UK studies, which fail to detect any direct wage effects associated with school quality.

The results presented in chapter 3 suggest that policies aimed at improving the quality of education through factors such as the number of pupils per teacher may not be effective in terms of improving an individual's position within the labour market. Despite the existence of relatively strong quality effects in the US, studies in the UK have failed to detect any significant wage enhancing effects associated with quality. The results should, however, be interpreted with caution since in the UK, there are few sources of data offering information relating to school quality which may be matched to individuals. Another limitation of the empirical analysis undertaken in chapter 3 is that there are relatively few controls for environmental factors which may influence the estimates of the LEA-specific returns to education. In particular, it is difficult to obtain variables relating to average levels of wealth that exist within each LEA. Using data from the entire NCDS cohort, an attempt was made to control for mean family income and mean parental education, but these derived variables were generally found to exert little impact on the estimated rates of return. Some evidence was found, however, to suggest that LEAs segregating students according to ability are associated with a higher rate of return to schooling. Local authorities with a high degree of selection, captured by the proportion of students attending grammar schools, were observed with higher rates of return. This may suggest that segregation according to ability is beneficial to both the most able and less able students within an LEA.

Concentrating on the wage effects associated with schooling provides one way of testing some of the central predictions of the theory of human capital accumulation. Once the period of full time schooling has been completed, the theory predicts that workers continue to invest in new skills while employed within a job. With the incentive to invest declining as the worker moves through their working life, the relationship between earnings and years of labour market experience is predicted to be concave. One of the most significant findings in the empirical literature relating to the determination of earnings is that the return per year of experience is estimated to be positive. This is generally considered as providing evidence in support of the theory of human capital. Models of job mobility, however, are also capable of predicting that the return to experience is positive even if no investment in human capital occurs. These models move away from the perfectly competitive framework of human capital theory and assume that the labour market is characterised by factors such as imperfect information and heterogeneity among firms and workers. There are various approaches to modelling the process of mobility, but all predict that in the long run, the wage gain associated with voluntary mobility will be positive. These approaches, however, do present differing insights into the way that the positive long run wage gain is generated. Mobility may induce an upward shift in the earnings-experience profile at the point of job change, or increase the gradient of the profile if a worker switches into a job with a higher rate of on-the-job wage growth.

Chapter 4 referred to an alternative data set, the British Household Panel Survey, in order to estimate the wage effects associated with job mobility. By making use of the panel nature of the data, it was possible to identify an individual's mobility behaviour in three separate time intervals. Given information relating to job changes occurring in the past, current, and future periods, it was possible to estimate the wage gains arising from mobility in the current period, while correcting for the bias attributable to unobserved heterogeneity between job movers and stayers. The results obtained from estimating a wage change equation over the period 1991-94 revealed that the total gain associated with mobility was approximately 11% for men and 9% for women. Further interpretation of the results suggested that for men, around three-quarters of this gain was due to the movement onto a steeper earnings profile, and one-quarter due to the earnings profile shifting upwards at the point of job change. For women, approximately half of the total gain could be attributed to each of the two individual wage effects. These results would appear to indicate that there exists significantly positive wage gains associated with switching jobs. For individuals who undertake a series of job changes in their working life, therefore, the conventional estimate of the return to experience could also incorporate the wage effects associated with mobility in addition to the return on human capital investments. Evidence from previous research, however, suggests that the return to mobility is only positive for voluntary job changes. The estimates obtained in chapter 4 are interpreted as wage gains arising from voluntary mobility since the wage change equation was only estimated for those who worked continuously over the three year period. By also including those who switched jobs with an intervening spell of unemployment, a relatively large wage penalty was observed for these involuntary movers. This distinction between voluntary and involuntary mobility may not be precise and so further research would be required to fully understand the wage effects associated with these two types of job changes. It would also be worthwhile to distinguish between job changes that occur within the same firm and across firms, as the effect on earnings may differ among such groups of movers. For women, it may also be important to identify separately job changes that occur for family reasons since such mobility may be distinct from other forms of voluntary and involuntary job changes. All of these issues could potentially be explored in further research into the effect that labour mobility has on the earnings of workers over time.

Appendix A

The investment ratio

The cost of investing in human capital is given by the following cost function:

$$C\left[x(t), K(t), t\right] = wx(t)K(t)$$

The net benefit of an investment made at t is then given by:

$$NB\left[x(t), K(t), t\right] = Ax(t)^{b} K(t)\frac{w}{r+\delta}\left[1-e^{-(r+\delta)(T-t)}\right] - wx(t)K(t)$$

The optimal value of $x(t)$ is then found by differentiating net benefit with respect to $x(t)$ and setting this derivative equal to zero. This then gives:

$$x_{CP}^{*}(t) = \left\{\frac{Ab}{r+\delta}\left[1-e^{-(r+\delta)(T-t)}\right]\right\}^{\frac{1}{1-b}}$$

The first derivative of this is given by:

$$\frac{dx_{CP}^{*}(t)}{dt} = -\frac{1}{1-b}\left\{\frac{Ab}{r+\delta}\left[1-e^{-(r+\delta)(T-t)}\right]\right\}^{\frac{b}{1-b}} Abe^{-(r+\delta)(T-t)} \qquad \text{(A.1)}$$

The second derivative is:

$$\frac{d^{2}x_{CP}^{*}(t)}{dt^{2}} = -\left\{\frac{Ab}{r+\delta}\left[1-e^{-(r+\delta)(T-t)}\right]\right\}^{\frac{b}{1-b}} \frac{Ab(r+\delta)}{1-b}e^{-(r+\delta)(T-t)}$$
$$+\frac{Ab}{1-b}e^{-(r+\delta)(T-t)}\frac{b}{1-b}\left\{\frac{Ab}{r+\delta}\left[1-e^{-(r+\delta)(T-t)}\right]\right\}^{\frac{b}{1-b}-1} Abe^{-(r+\delta)(T-t)}$$

The overall sign of the second derivative will depend upon the magnitudes of the two terms on the right-hand-side, one of which is negative and the other positive. The size of these two terms changes over time and the second derivative will become positive when:

$$\frac{Ab}{1-b}e^{-(r+\delta)(T-t)}\frac{b}{1-b}\left\{\frac{Ab}{r+\delta}\left[1-e^{-(r+\delta)(T-t)}\right]\right\}^{\frac{b}{1-b}-1} Abe^{-(r+\delta)(T-t)}$$
$$\succ\left\{\frac{Ab}{r+\delta}\left[1-e^{-(r+\delta)(T-t)}\right]\right\}^{\frac{b}{1-b}} \frac{Ab(r+\delta)}{1-b}e^{-(r+\delta)(T-t)}$$
$$\Rightarrow e^{-(r+\delta)(T-t)} \succ 1-b \qquad \text{(A.2)}$$

For the case of individuals with intermittent participation, the optimal investment ratio in any period prior to the break occurring is:

$$x_{IP}^{*}(t) = \left\{\frac{Ab}{r+\delta}\left[1+e^{-(r+\delta)(c-t)} - e^{-(r+\delta)(g-t)} - e^{-(r+\delta)(T-t)}\right]\right\}^{\frac{1}{1-b}}$$

The first derivative is:

$$\frac{dx_{IP}^{*}(t)}{dt}=\frac{1}{1-b}\left\{\frac{Ab}{r+\delta}\left[1+e^{-(r+\delta)(c-t)}-e^{-(r+\delta)(g-t)}-e^{-(r+\delta)(T-t)}\right]\right\}^{\frac{b}{1-b}}$$
$$\times Ab\left[e^{-(r+\delta)(c-t)}-e^{-(r+\delta)(g-t)}-e^{-(r+\delta)(T-t)}\right]$$

It may be shown in a similar way to the case of continuous participation that the second derivative will be positive when:

$$-\left[e^{-(r+\delta)(c-t)}-e^{-(r+\delta)(g-t)}-e^{-(r+\delta)(T-t)}\right]\succ 1-b \qquad \text{(A.3)}$$

By comparing the conditions for the investment profile to be convex for the two cases, it may be seen that the profile for those with intermittent participation will become convex at an earlier date since the term on the left-hand-side in (A.3) will always be greater than that in (A.2) at a point in time. The value of the optimal investment ratio at the point where the profiles become convex, however, will be the same in both cases, which may be seen by using (A.3) and (A.2) in the relevant equations for the optimal investment ratios. Points on the investment profile for those with continuous participation will appear on the profile for those with intermittent participation at an earlier date.

Earnings

An individual's earnings at time t is: $y(t)=[1-x(t)]wK(t)$ (A.4)

The following differential equation gives the human capital stock at t:

$$\frac{dK(t)}{dt}=I(t)-\delta K(t)$$

Substituting in for the production function (2.2) and dividing through by K(t) gives:

$$\frac{dK(t)/dt}{K(t)}=Ax(t)^{b}-\delta$$

Integrating both sides:

$$\log K(t)=\log K_{0}+\int_{\tau=0}^{t}\left[Ax(\tau)^{b}-\delta\right]d\tau \qquad \text{(A.5)}$$

where K_0 is the initial stock of human capital

Taking the log of (A.4) gives: $\log y(t)=\log[1-x(t)]+\log w+\log K(t)$ (A.6)

Using (A.5) in (A.6) implies:

$$\log y(t)=\log(wK_{0})+\log[1-x(t)]+\int_{\tau=0}^{t}\left[Ax(\tau)^{b}-\delta\right]d\tau \qquad \text{(A.7)}$$

For s years of schooling where the optimal investment ratio is equal to one, (A.7) may be rewritten as:

$$\log y(t) = \log(wK_0) + \log[1-x(t)] + \int_{\tau=0}^{s} \left[A(1)^b - \delta\right] d\tau + \int_{\tau=s}^{t} \left[Ax(\tau)^b - \delta\right] d\tau$$
$$= \log(wK_0) + s(A-\delta) + \log[1-x(t)] + \int_{\tau=s}^{t} \left[Ax(\tau)^b - \delta\right] d\tau \qquad \text{(A.8)}$$

The growth in earnings may then be expressed as:

$$\frac{d\log y(t)}{dt} = -\frac{dx^*(t)/dt}{1-x^*(t)} + Ax^*(t)^b - \delta \qquad \text{(A.9)}$$

The difference between the optimal investment ratios of continuous and intermittent participants

The optimal investment ratio for a continuous worker is:

$$x^*_{CP}(t) = \left\{\frac{Ab}{r+\delta}\left[1-e^{-(r+\delta)(T-t)}\right]\right\}^{\frac{1}{1-b}}$$

For ease of exposition, this may be rewritten as:

$$x^*_{CP}(t) = \left\{B_1\left[1-e^{-B_2(T-t)}\right]\right\}^{\frac{1}{1-b}} \text{ where } B_1 = \frac{Ab}{r+\delta}\text{, and } B_2 = (r+\delta)$$

Using this notation, the optimal investment ratio of an intermittent worker is:

$$x^*_{IP}(t) = \left\{B_1\left[1+e^{-B_2(g+L-t)} - e^{-B_2(g-t)} - e^{-B_2(T-t)}\right]\right\}^{\frac{1}{1-b}} \text{ where } L = c-g \text{ (length of break)}$$

This can be expressed as:

$$x^*_{IP}(t) = \left\{B_1\left[1+e^{-B_2(g-t)}(e^{-B_2L}-1) - e^{-B_2(T-t)}\right]\right\}^{\frac{1}{1-b}}$$
$$= \left\{B_1\left[1-e^{-B_2(T-t)}\right] - B_1e^{-B_2(g-t)}\left[1-e^{-B_2L}\right]\right\}^{\frac{1}{1-b}}$$

Then using the expression for continuous participants above:

$$x^*_{IP}(t) = \left\{x^*_{CP}(t)^{(1-b)} - B_1e^{-B_2(g-t)}\left[1-e^{-B_2L}\right]\right\}^{\frac{1}{1-b}}$$

$$x^*_{IP}(t)^{(1-b)} = \left\{x^*_{CP}(t)^{(1-b)} - B_1e^{-B_2(g-t)}\left[1-e^{-B_2L}\right]\right\}$$

$$x^*_{CP}(t)^{(1-b)} - x^*_{IP}(t)^{(1-b)} = B_1e^{-B_2(g-t)}\left[1-e^{-B_2L}\right]$$

Solving for the number of periods spent in schooling

For continuous participants:

$$x_{CP}^{*}(t) = \left\{B_1\left[1 - e^{-B_2(T-t)}\right]\right\}^{\frac{1}{1-b}}$$

The left-hand-side will equal one at the time the individual leaves full time education ($t = S_{CP}$), giving:

$$1 - \frac{1}{B_1} = e^{-B_2(T-S_{CP})}$$

Taking natural logs:

$$\ln\left(1 - \frac{1}{B_1}\right) = -B_2\left(T - S_{CP}\right)$$

$$S_{CP} = T + \frac{\ln\left(1 - 1/B_1\right)}{B_2} \qquad \text{(A.10)}$$

Using the same method, it may be shown for the case of intermittent participation that the number of periods devoted to full time schooling is:

$$S_{IP} = T + \frac{1}{B_2}\ln\left(1 - 1/B_1\right) - \frac{1}{B_2}\ln\left[1 + e^{B_2(T-g)} - e^{B_2(T-g-L)}\right] \qquad \text{(A.11)}$$

The first derivatives of this are:

$$\frac{\delta S_{IP}}{\delta g} = \left[1 + e^{B_2(T-g)} - e^{B_2(T-g-L)}\right]^{-1}\left[e^{B_2(T-g)} - e^{B_2(T-g-L)}\right] \qquad \text{(A.12)}$$

This is positive implying that the later the break (the higher is g) the greater is the time spent in education

$$\frac{\delta S_{IP}}{\delta L} = -\left[1 + e^{B_2(T-g)} - e^{B_2(T-g-L)}\right]^{-1} e^{B_2(T-g-L)} \qquad \text{(A.13)}$$

This is negative implying that the longer the break the lower is the time spent in education

Appendix B

List of LEAs and estimated rates of return to schooling from equation (3.7)

LEA	*NAME*	*RATE OF RETURN*	*LEA*	*NAME*	*RATE OF RETURN*
1	Cheshire	0.105	36	Tynemouth	0.098
2	Lancashire	0.100	37	Tees-side	0.119
3	Southport	0.104	38	York, E. Riding	0.093
4	Wigan	0.097	39	York, W. Riding	0.101
5	Birkenhead	0.091	40	Kingston-upon-Hull	0.096
6	Chester	0.092	41	Barnsley	0.084
7	Stockport	0.097	42	Bradford	0.096
8	Wallasey	0.073	43**	Dewsbury	
9	Barrow-in-Furness	0.095	44	Doncaster	0.129
10	Blackburn	0.063	45	Halifax	0.111
11	Blackpool	0.100	46	Huddersfield	0.097
12	Bolton	0.102	47	Leeds	0.098
13**	Bootle		48	Rotherham	0.085
14	Burnley	0.096	49	Sheffield	0.103
15	Bury	0.084	50	Wakefield	0.091
16	Liverpool	0.112	51	York	0.104
17	Manchester	0.100	52	Derbyshire	0.101
18**	Oldham		53	Leicestershire	0.107
19	Preston	0.110	54	Lincoln, Holland	0.123
20	Warrington	0.100	55	Lincoln, Kesteven	0.114
21	Rochdale	0.185	56	Lincoln, Lindsey	0.095
22	St Helens	0.106	57	Northamptonshire	-0.003
23	Salford	0.140	58	Nottinghamshire	0.102
24	Cumberland	0.101	59	Rutland	0.106
25	Durham	0.100	60	Derby	0.105
26	Northumberland	0.098	61	Leicester	0.116
27	Westmorland	0.121	62	Grimsby	0.099
28	York, N. Riding	0.099	63	Lincoln	0.105
29	Carlisle	0.096	64	Northampton	0.105
30	Darlington	0.107	65	Nottingham	0.108
31	Gateshead	0.112	66	Bedfordshire	0.098
32	South Shields	0.102	67	Luton	0.103
33	Sunderland	0.101	68	Cambridge, Isle of Ely	0.111
34	Hartlepool	0.109	69	Essex	0.102
35	Newcastle-upon-Tyne	0.108	70	Hertfordshire	0.094

LEA	*NAME*	*RATE OF RETURN*	*LEA*	*NAME*	*RATE OF RETURN*
71	Huntingdon, Peterboro'	0.095	110**	Exeter	
72	Norfolk	0.096	111	Plymouth	0.085
73	Suffolk East	0.121	112	Bristol	0.080
74	Suffolk West	0.104	113	Gloucester	0.102
75	Great Yarmouth	0.095	114	Bath	0.094
76	Norwich	0.105	115	Torbay	0.109
77	Ipswich	0.106	116*	Radnor	
78	Southend-on-Sea	0.092	117	Brecon	0.070
79	Kent	0.093	118	Carmarthen	0.076
80	Inner London	0.094	119	Glamorgan	0.090
81 (+)	Outer London	0.094	120	Monmouth	0.099
82 (+)	Bexley, Bromley	0.101	121**	Anglesey	
83 (+)	Formerly Middlesex	0.100	122	Caernarvon	0.085
84 (+)	Formerly Surrey	0.074	123	Cardigan	0.080
85*	Newham, W. Ham		124	Denbigh	0.098
86	Croydon	0.110	125	Flint	0.100
87	Surrey	0.101	126*	Merioneth	
88	East Sussex	0.086	127	Montgomery	0.070
89	West Sussex	0.095	128	Pembroke	0.095
90	Canterbury	0.138	129	Cardiff	0.107
91	Brighton	0.094	130	Merthy Tydfil	0.075
92*	Eastbourne		131	Swansea	0.112
93	Hastings	0.094	132	Newport	0.150
94	Berkshire	0.093	133	Herefordshire	0.092
95	Buckinghamshire	0.101	134	Shropshire	0.102
96	Dorset	0.105	135	Staffordshire	0.102
97	Oxfordshire	0.083	136	Warwickshire	0.107
98	Hampshire	0.093	137	Solihull	0.111
99	Isle of Wight	0.081	138	Worcestershire	0.109
100	Reading	0.098	139	Burton-upon-Trent	0.117
101	Oxford	0.079	140	Warley	0.101
102	Bournemouth	0.097	141	Stoke-on-Trent	0.102
103	Portsmouth	0.080	142	Walsall	0.114
104	Southampton	0.088	143	West Bromwich	0.099
105	Cornwall	0.093	144	Woverhampton	0.099
106	Devon	0.094	145	Birmingham	0.112
107*	Gloucestershire		146	Coventry	0.113
108	Somerset	0.089	147	Dudley	0.113
109	Wiltshire	0.092	148	Worcester	0.092

* Unable to estimate LEA return for men due to missing earnings data, or entry age (LEA126)

** Unable to estimate LEA return for men because of missing regional data in 1991

+ For these LEAs, NCDS and CIPFA differ. Bexley and Bromley are identified individually in CIPFA whereas in NCDS they are combined. For the mapping in of the CIPFA quality measures, the average of Bexley and Bromely was taken. For Outer London the average CIPFA values for Barking, Ealing, Harringey, Havering, Redbridge and Waltham Forest are used. Formerly Middlesex is the average of Barnet, Brent, Enfield, Harrow, Hillingdon and Hounslow. Formerly Surrey consists of Merton, Richmond, Sutton and Kingston, which are all individually identified in the CIPFA data.

Description of variables

Variables within the earnings equation

LNPAY	Usual gross weekly pay in 1991 job (dependent variable)
S	Age at which first job started; or total years in education between 16 and 23
SIZE1-9	Number of employees at current place of work; *SIZE1*=1-10, *SIZE2*=11-25, *SIZE3*=26-99, *SIZE4*=100-499, *SIZE5*=500+, *SIZE9*=unavailable
MARRIED	Equals one if reported being married in 1991; *MARMISS*=1 if unknown
UNION	Equals one if reported being union member in 1991; *UNIMISS*=1 if unknown
REGION1-11	Region of residence in 1991; 1=North, 2=North West, 3=Yorkshire and Humberside, 4=West Midlands, 5=East Midlands, 6=East Anglia, 7=South West, 8=South East, 9=London, 10=Wales, 11=Scotland
LEA1-148	Local authority at age 11; see previous table for coding information
ABILITY1-10	Ten dummy variables indicating score on verbal and non verbal tests taken at age 11. Maximum score is 80, which is split into ten ranges of scores

Variables within the quality equation

CIPFAPTR	Number of pupils per teacher in LEA in the year ending March 1970
CIPFASAL	Average teacher salary in LEA in 1970
CIPFAEXP	Total expenditure per pupil in LEA in 1970
CIPFAPOP	Population per acre in LEA in 1970
MNGRAM	Proportion of individuals attending grammar schools within LEA in 1974
MNBOYS	Proportion of individuals attending all boys schools within LEA in 1974
MNMEALS	Proportion of children receiving free school meals in LEA at age 11 (1969)
MNFAMINC	Mean family net income in LEA in 1974. Derived from mother's, father's, and other sources of income. Each source of income is given as a number reflecting a particular range of earnings e.g. £0-17. Midpoints of these ranges were used to construct an overall measure of monthly income in £ for each cohort member. The average was then taken for those living in each LEA.
MNMEDUC	Mean educational attainment of mother in LEA. This is derived from an NCDS variable taking a value between 1 (left school at under 13 years of age) and 10 (left education beyond age 23)
MNFEDUC	Mean education attainment of father in LEA. Derived as above.

AREA1-10 Dummy variables indicating region of the country in which the LEA at age 11 was located; 1=North Western, 2=Northern, 3=East and West Riding, 4=North Midlands, 5=Eastern, 6=London and South East, 7=Southern, 8=South West, 9=Midlands, 10=Wales

Variables used in the additional estimations

S Number of years spent in full time education between ages 16 and 23

QUAL0-9 Highest qualification obtained between ages 23 and 33
0 = no qualifications
1 = CSE
2 = O Level
3 = GCSE
4 = A Level
5 = Scottish qualification
6 = RSA, C&G
7 = Professional qualification
8 = Degree
9 = Other

Appendix C

Further description of the statistical model

The model estimated in this study is essentially the same as that described by Holmlund (1984) and Keith and McWilliams (1997). The earnings of an individual *i* in the years *t* and *t*+3 may be expressed as

$$\ln W_{i,t} = \alpha_1 + \beta_1 X_{i,t} + \varepsilon_{i,t} \quad (C.1)$$

$$\ln W_{i,t+3} = \alpha_2 + \beta_2 X_{i,t+3} + \varepsilon_{i,t+3} \quad (C.2)$$

Subtracting (C.1) from (C.2) then gives

$$\Delta \ln W_i = \alpha_2 - \alpha_1 + \beta_2 X_{i,t+3} - \beta_1 X_{i,t} + \varepsilon_{i,t+3} - \varepsilon_{i,t} \quad (C.3)$$

Keith and McWilliams then suggest adding and subtracting the term $\beta_2 X_{i,t}$ to the right-hand-side of (C.3).

$$\Delta \ln W_i = \alpha_2 - \alpha_1 + \beta_2 X_{i,t+3} - \beta_2 X_{i,t} + \beta_2 X_{i,t} - \beta_1 X_{i,t} + \varepsilon_{i,t+3} - \varepsilon_{i,t}$$

$$\Delta \ln W_i = \alpha_2 - \alpha_1 + \beta_2 \Delta X_i + (\beta_2 - \beta_1) X_{i,t} + \varepsilon_{i,t+3} - \varepsilon_{i,t} \quad (C.4)$$

Using Holmlund's assumption that the coefficients in the wage level equations are linearly related

$$\beta_2 = \beta_1 + \delta\beta_1 \quad (C.5)$$

If δ is equal to zero then the coefficients remain constant over time but if δ is negative then the *X* coefficient values decline over time. Rearranging (C.5) gives

$$\beta_2 - \beta_1 = \delta\beta_1 \quad (C.6)$$

Substituting (C.6) into (C.4)

$$\Delta \ln W_i = \alpha_2 - \alpha_1 + \beta_2 \Delta X_i + \delta\beta_1 X_{i,t} + \varepsilon_{i,t+3} - \varepsilon_{i,t} \quad (C.7)$$

From (C.1)

$\ln W_{i,t} - \alpha_1 - \varepsilon_{i,t} = \beta_1 X_{i,t}$ which multiplied by δ gives

$$\delta \ln W_{i,t} - \delta\alpha_1 - \delta\varepsilon_{i,t} = \delta\beta_1 X_{i,t} \quad (C.8)$$

Substituting (C.8) into (C.7)

$$\Delta \ln W_i = \alpha_2 - \alpha_1 + \beta_2 \Delta X_i + \delta \ln W_{i,t} - \delta\alpha_1 - \delta\varepsilon_{i,t} + \varepsilon_{i,t+3} - \varepsilon_{i,t}$$

$$\Delta \ln W_i = \alpha_2 - \alpha_1(1+\delta) + \beta_2 \Delta X_1 + \delta \ln W_{1,t} + \varepsilon_{i,t+3} - \varepsilon_{i,t}(1+\delta)$$

$$\Delta \ln W_i = \alpha_0 + \beta_2 \Delta X_i + \delta \ln W_{i,t} + \varepsilon_i^* \quad (C.9)$$

where $\alpha_0 = \alpha_2 - \alpha_1(1+\delta)$ and $\varepsilon_i^* = \varepsilon_{i,t+3} - \varepsilon_{i,t}(1+\delta)$

The problem with estimating equation (C.9) is that it is likely that the composite error term will be correlated with the value of earnings in the initial period. In terms of (C.1) a positive shock to the error term $\varepsilon_{i,t}$ will raise the natural log of initial earnings which means that in (C.9) there may exist correlation between the composite error ε_i^* and initial earnings which appears as a right-hand-side variable.

Obtaining predicted values for initial pay

Variable	Male coefficients and *t*-ratios	Female coefficients and *t*-ratios
AGE	0.094 (9.601)	0.084 (6.244)
AGESQ	-0.001 (8.445)	-0.001 (5.876)
TENURE	-0.005 (0.830)	0.017 (1.889)
TENURESQ	0.000 (0.487)	-0.001 (1.740)
EDUC1 (lowest)	0.181 (3.363)	0.129 (1.717)
EDUC2	0.171 (3.343)	0.243 (4.180)
EDUC3	0.275 (5.524)	0.305 (4.281)
EDUC4	0.377 (7.993)	0.495 (8.076)
EDUC5 (highest)	0.555 (10.694)	0.748 (12.232)
MARRIED	0.122 (4.137)	-0.070 (2.035)
UNEMP	0.095 (0.755)	0.065 (0.335)
HOURS	0.005 (1.689)	0.010 (2.152)
constant	3.567 (2.437)	3.879 (2.674)
R-squared	0.4075	0.3981
F	20.28	14.67
N	965	588

Table 4.6 Equation used to obtain predicted values of 1991 log earning
EDUC0 (no qualifications is excluded)
Also included are 17 dummy variables capturing region of residence in 1991

AGE	age at the time of 1991
AGESQ	age at 1991 squared
TENURE	years in current job
TENURESQ	years in current job squared
EDUC0	no qualifications
EDUC1	commercial, cse, apprenticeship, other
EDUC2	O level
EDUC3	A level
EDUC4	teaching, nursing, other higher
EDUC5	degree, higher degree
MARRIED	equals one if married in 1991
UNEMP	regional unemployment
HOURS	usual hours worked per week in current job

Additional summary statistics

Sample	*Men*			*Women*		
	N	*AGE*	*TENURE*	N	*AGE*	*TENURE*
ALL	965	35.509 (9.726)	5.471 (6.169)	588	35.282 (10.30)	4.048 (4.989)
CMOVER	332	32.410 (9.056)	3.685 (4.399)	233	32.996 (9.600)	2.973 (3.830)
PMOVER	159	35.736 (10.01)	1.431 (0.431)	122	34.533 (10.17)	1.373 (0.843)
FMOVER	90	37.233 (9.117)	8.008 (5.634)	40	37.575 (9.451)	7.745 (4.830)
PFMOVER	95	32.084 (8.891)	1.252 (0.855)	67	31.284 (9.234)	1.211 (0.815)
STAYER	289	39.533 (9.146)	10.343 (7.093)	126	41.635 (9.654)	8.960 (6.259)

Table 4.7 Means and standard deviations for age in 1991 and years of tenure in the current job in 1991 for males and females observed as working continuously between 1991 and 1994

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