Education, Training and Earnings in Australia and Britain

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Abstract

One of the key topics in the empirical education and training literature at the present time concerns how one correctly measures the causal impact of education and training on earnings. The central issue concerns how one appropriately controls for the fact that education and training outcomes are not randomly assigned across the population. Education and training outcomes are endogenous, being the result of individual choices, attributes and circumstances. Estimates of the returns to education and training which ignore this endogeneity may be biased. These biases arise because of correlation between unobserved individual characteristics such as ability or family attributes which determine education and training outcomes as well as wages.

This thesis uses panel data from the Australian Longitudinal Survey (ALS), Australian Youth Survey (AYS) and British National Child Development Survey (NCDS) to estimate the economic returns to different types of education and training in Australia and Britain. These particularly rich data sets allow us to directly compare the advantages and disadvantages of the different estimation techniques which been devised to deal with the endogeneity of education and training. In particular we compare instrumental variable, fixed effect and proxy methods. Instrumental variable techniques require us to identify at least one variable which affects education or training, but not wages controlling for education and training. Fixed effect methods assume that the unobserved individual attributes are fixed (over time or within families) and use econometric models which difference out this fixed effect. Proxy methods require access to data which has explicit proxies for

things like ability or family attributes. The data used in this thesis allows us to exploit each of these techniques.

We find that education and training confer significant wage advantages on individuals. The actual size of the estimated returns, however, depends on the estimation procedure used. The results we obtain suggest that standard estimates which do not correct for the endogeneity of education and training generally underestimate the returns to education and training for both men and women in Australia and Britain.

The thesis also examines gender wage differentials and looks at the role education and training plays in explaining these differences. We find that gender wage differentials generally decrease with education. We also find that part of the observed difference in the wages of men and women is due to the fact that men receive more work related training than women once in work.

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Declaration

1. No part of this thesis has been presented to any University for any degree.

2. Subsections 2.4.2 and 2.5.2 of Chapter 2 and all of Chapter 6 were undertaken as joint work with Richard Blundell and Costas Meghir.

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Abbreviations

ALS	Australian Longitudinal Survey
BNSG	British National Survey of 1980 Graduates
BSAS	British Social Attitudes Survey
CPS	US Current Population Survey
EOPP	US Employment Opportunities Pilot Projects Survey
EPTC	Employer Provided Training Course
GHS	General Household Survey
GTC	Government Training Course
NCDS	National Child Development Survey
NLS	US National Longitudinal Surveys
NLSY	US National Longitudinal Survey of Youth
NSGD	British National Survey of Graduates and Diplomats
NTS	National Training Survey
PTC	Private Training Course
QTC	Qualification Training Course
TFP	Total Factor Productivity
YTS	Youth Training Scheme
WRTC	Non Qualification Work Related Training Course

Contents

List of Tables

List of Figures

Chapter 1

Introduction

This thesis uses panel data from the Australian Longitudinal Survey (ALS), Australian Youth Survey (AYS) and British National Child Development Survey (NCDS) to look at the relationship between education, training and earnings in Australia and Britain. Education and training outcomes are not randomly assigned across the population. They are a result of individual choices, circumstances and attributes, and if we ignore this endogeneity our estimates of the returns to education and training may be biased. These biases arise because of correlation between unobserved individual characteristics such as ability and family attributes which determine education and training outcomes as well as wages.

There have been three main methods proposed in the economic literature for correcting for this endogeneity bias. The first method involves directly proxying these unobserved individual attributes. This generally requires access to data which has explicit proxies for things like ability or family attributes. A second approach relies on correcting for endogeneity using instrumental variable techniques. This requires identifying at least one variables which affects education or training, but not wages controlling for education or training. The final method involves using fixed effect estimation techniques. This method assumes that the unobserved attributes are fixed over time and uses wage information from different periods of time to difference out this fixed effect. This method can only be used if we observe wages both before and after the education or training takes place. A variant of the fixed effect method which has been used in the literature, is to assume that these unobserved attributes are the same for twins or siblings and that they can be differenced out by looking at the relationship between the differences in education and differences in earnings of siblings.

The particularly rich data used in this thesis allows us to directly compare estimates of the returns to education and training using all of these different econometric techniques. It also allows us to estimate returns for both men and women.

The Australian panel data we use comes for the Australian Longitudinal Survey (ALS) and Australian Youth Survey (AYS). These surveys are similar in structure to the US National Longitudinal Survey of Youth (NLSY). The ALS commenced in 1985, with 8995 people aged from 16 to 25 selected randomly across Australia. This group was re–interviewed annually until 1988 with a subset of the original group (those aged 16–20 in 1985) interviewed up until 1991. The AYS began in 1989 and interviewed a nationally representative group aged 16 to 19 years. This group have been re–interviewed annually and the latest available data is for 1993. In each year a new cohort of 16 year olds has been added to the survey. In this thesis we focus on individuals aged between 16 and 25 and use data from both surveys for the seven years between 1985 and 1991. Both surveys have detailed information on the persons' family background, schooling experience, post–school education and training, transition to work and labour market experience.

The National Child Development Survey (NCDS) is a continuing longitudinal survey of persons living in Great Britain who were born between 3 and 9 March, 1958. There have been 5 waves of the NCDS. These were carried out in 1965 (NCDS1 when the cohort members were aged 7), in 1969 (NCDS2 when they were aged 11), in 1974 (NCDS3 when they were aged 16), in 1981 (NCDS4 when they were aged 23) and in 1991 (NCDS5 when they were aged

33). There is also information in 1978 from individuals schools on exam results (CSE, O and A levels). The NCDS also has detailed information on the individual's family background, schooling experience, ability and educational attainment as well as labour market experience including training.

The thesis is organised as follows. In Chapter 2 we review the theoretical and empirical literature which has looked at the relationship between education, training and earnings. The Chapter begins by looking at the theoretical models which have been developed to explain the observed relationship between education, training and earnings. We then move on to look at the methodological issues involved in estimating the returns to education and training. This primarily concerns how one can appropriately control for the fact that education and training are endogenous. We conclude the Chapter by reviewing the empirical literature which has looked at the relationship between education, training and earnings.

Chapter 3 looks at the early returns to formal educational outcomes in Australia using both the ALS and AYS. The Chapter uses instrumental variable techniques to deal with the endogeneity of education. We argue that an individual's position in the family in terms of how many older siblings they have is a crucial factor in determining educational outcomes in Australia, controlling for family size and year of birth. We show that individuals with more older siblings, have significantly less education than individuals from similarly sized families with less older siblings. Moreover, an individual's birth order is exogenous given family size. We argue that the number of older siblings, has no legitimate role in a wage equation, controlling for education and family size. We therefore exploit this exogenous influence on the education decision and use the number of older siblings as an instrument for education in various wage equations which estimate the returns to education.

Chapter 4 also looks at the early returns to formal education in Australia using a sample of siblings drawn from the ALS and AYS data used in Chapter 3. We begin the Chapter by carrying out the same IV estimation procedure used in Chapter 3 and comparing these results with those obtained for our whole sample in Chapter 3. We then compare these results with estimation procedures which assume that unobserved individual characteristics which determine wages are fixed within families. The first method involves proxying the family effect using information from both of the siblings. The second involves using a within family fixed effect estimation procedure. Both methods potentially allow us to identify biases caused by the correlation of education with unobserved family attributes which determine wages. We then go on to compare the results obtained using IV and within family methods.

In Chapter 5 we look at the returns to education for our British cohort from the National Child Development Survey, but specifically focus on the problem of omitted–ability bias and the affect this has on estimates of the returns to education. Our NCDS data has detailed information on ability tests undertaken when the individual was 7 as well as family background variables, information from the individual's teacher, formal education outcomes and labour market experience.

We begin the Chapter by ignoring ability, and once again use instrumental variable techniques. Unobserved ability is only one of the possible reasons why the unobserved determinants of wages and schooling may be correlated and to control for this possibility we once again rely on instrumental variable techniques. The instruments we use in this Chapter include family composition variables such as birth order and the sex composition of the individual's siblings. They also include the teacher's assessment of parental interest in the child's education when they were aged seven. We argue that these parental interest variables, have no role in a wage equation controlling for education and can be used as instruments for education. We then move on to consider the question of omitted ability bias and include proxies of ability in our wage equations. We end the Chapter by looking at how the results are affected when we control for both omitted ability and other correlated individual effects.

Chapter 6 looks at the returns to different forms of work related training in Britain. A number of issues are addressed in this Chapter. We look at whether the estimated returns to education which were estimated in Chapter 5 may be are on account of not taking into account subsequent periods of work related training. We also look at whether the returns to various types of work related training vary for individuals with different educational backgrounds. The econometric models we develop allow us to control for the fact that training may be correlated with both transitory shocks to wages and permanent fixed effects such as ability. This involves using instrumental variable, proxy and fixed effect estimation procedures.

Throughout the thesis, we also focus on gender wage differentials, and specifically look at how these vary across educational groups. Observed differences in the wages received by men and women generally decrease with education. We also decompose these observed differences in male and female wages into that attributable to differences in observed characteristics, and that attributable to the observed characteristics of women being valued differently to those of men. We also look at how important the differences in the work related training experiences of men and women are in explaining the observed differences in the wages received by men and women, across different education groups.

Chapter 7 draws conclusions from the work undertaken in the thesis and suggest areas for further research.

Chapter 2

Education, Training, and Earnings: A Critical Survey

2.1 Introduction

In this chapter we survey the literature dealing with the relationship between education, training, and earnings. In the first section of the chapter we focus on the theoretical issues underpinning the economics of education and training. In the next section we move onto examine some of the theoretical models which have been used in the literature to explain *individuals'* education and training investment decisions. These models tend to focus on the private returns to individuals from investing in education and/or training under different assumptions. Education and training has also been argued to provide social returns to the economy and it is these social returns which have, in part, been used to justify government spending on education and training. Theoretical issues associated with the social returns to education and training are briefly discussed at the end of the section.

In the next section of the chapter, we review the literature which has dealt with the methodological issues involved in estimating the returns to education and training. The literature in this area has focused on how we can estimate *unbiased* estimates of the returns to different forms of education and training in terms of earnings or wage outcomes. The major issue here concerns how one appropriately controls for the fact that education and training outcomes are not randomly assigned across the population, but are based on individual choices, attributes and circumstances. Because of this endogeneity, the *measured* earnings or wage differentials between people with different education and training backgrounds may over- or under-state the true causal effect of education and training. If, for example, individuals possess unobserved ability which is positively correlated with schooling and earnings, then estimates of the returns to schooling which do not take this into account will overstate the true effect of education on wage outcomes. If, on the other hand, a bad productivity shock leads to participation in a training scheme, then training becomes spuriously correlated with low wages and estimates which do not take this into account will under-estimate the true effect of this training. Biases in the estimated returns can also arise because the benefits of education and training are not always totally reflected in terms of monetary reward and because of measurement error in observed education and training.

In the final part of the chapter we critically review a selection of the empirical literature which has looked at the determinants and effects of education and training.

2.2 The Economic Analysis of Education and Training

2.2.1 Human Capital Approach

The idea that investment in human capital is similar to investment in physical capital dates back a long time in economic thought. Adam Smith [147, bk1, ch. 10, pt 1] wrote in 1776:

> When any expensive machine is erected, the extraordinary work to be performed by it before it is worn out, it must be ex-

> pected, will replace the capital laid out upon it, with at least the ordinary profits. A man educated at the expense of much labour and time to any of those employments which require extraordinary dexterity and skill, may be compared to one of those expensive machines. The work which he learns to perform, it must be expected, over and above the usual wages of common labour will replace to him the whole expense of his education, with at least the ordinary profits of an equally valuable capital. It must do this too in a reasonable time, regard being had to the very uncertain duration of human life, in the same manner as to the more certain duration of the machine.

The modern human capital approach, however, was pioneered by economists such as Jacob Mincer, Theodore Schultz and Gary Becker. It sees education and training as providing productivity augmenting skills that can be rented out to employers. Individuals invest in the amount of education and training which maximises the present discounted value of lifetime benefits net of investment costs.

Mincer's seminal piece in this area was published in 1958 in the *Journal of Political Economy* (see Mincer [126]) and questioned earlier studies which argued that variations in income across individuals was due primarily to differences in bequests and ability and luck. Mincer's work utilised the neoclassical production function and he constructed a model in which both interoccupational and intraoccupation earnings differentials could be explained on the basis of investment in human capital *in which the process of investment was subject to free choice.*

> The choice refers to training differing primarily in the length of time it requires. Since the time spent in training constitutes a postponement of earnings to a later age, the assumption of rational choice means an equalization of present values of life earnings

> at the time the choice is made.... Interoccupational differentials are therefore a function of differences in training.... Intraoccupation differences arise when the concept of investment in human capital is extended to include experience on the job[1].

Investment in human capital was the subject of Schultz's address to the American Economic Association in 1960 (see Schultz [144]). Schultz argued that in the absence of human capital considerations, it was difficult to explain the unexpectedly rapid post–war recovery in Europe given the large scale destruction of physical capital that had taken place. Schultz focused on five major forms of human capital investment: health facilities and services; on–the–job training by firms; formal school education and higher education; adult study programs; and migration to adjust to changing employment opportunities.

It was Gary Becker [18], however, who in 1964 undertook the most comprehensive and rigorous treatment of the subject of human capital and this work "has ever since served as the *locus classicus* on the subject" (see Blaug [28, p. 206]). In this work Becker formulated a model of on–the–job training, which he defined as training received from the person's employer whilst they are in work. He also extended his model to include schooling and other forms of human capital.

Becker's model recognised that an individual's human capital is affected by more that the level of education they have invested in. Ability and on–the–job training will also play a part. Becker distinguishes between *general* on–the–job training, which increases an individual's productivity to many employers equally, and *specific* on–the–job training, which increases an individual's productivity only at the firm in which the individual is employed.

He argues that the cost of *specific training*, is shared by the worker and the firm. The employee might be paid a wage greater than marginal product

[1] Mincer [126, p. 301].

during the training period, but after the training the employee's wage is below marginal product, although above what the employee could get elsewhere since the training only increases productivity in the current job. For *general training,* where the employees acquire skills which are productivity enhancing elsewhere, they alone pay for the training costs in terms of lower wages while they receive training. Their wage during training is equal to their marginal product at this time, which will be lower than their marginal product if they were not undertaking training because of the costs associated with the time spent off work and/or the need for supervision. They accept this lower wage because they expect that as a result of this training the present value of the stream of lifetime benefits net of this cost will be higher than if they hadn't undertaken the training. The reasons why individuals may undertake general on–the–job training is, therefore, very similar to the reasons why they may invest in formal education.

The human capital approach is consistent with observed age–earnings profiles which tend to rise rapidly early in a person's working career, then flatten out, and eventually fall. Human capital theory argues that earnings are low at first because of education and training investments and rise quickly as new skills are acquired. As people age, however, it is less profitable to make human capital investments since there is less time to capture possible returns. As an individual's skill acquisition slows, so too does the rate at which productivity increases and hence wages rise. Towards the end of a person's working life, skills start to depreciate due to lack of continued upgrading and this results in a drop in the earnings profile.

Human capital theory is also consistent with the observed fanning out of age–earnings profiles for people with different educational backgrounds. People who have above average ability are more likely to gain the most from investing in more education. They are, however, also more likely to learn quickly on–the–job and be presented with more on–the–job training opportunities. This tendency would explain why better–educated workers have age–earnings profiles which tend to be steeper and level off much later than less–well educated workers.

The early work of Mincer, Schultz and Becker has spurned a large amount of theoretical and empirical work. While a large amount of this work supports and extends the human capital approach, other work has been critical of its approach and assumptions. Some of this work is reviewed below.

2.2.2 The Screening Hypothesis

The Human Capital approach is based on the idea that education enhances productivity. However, it has been also argued in the literature that the wage premium associated with higher levels of education need not be related to higher productivity. The screening hypothesis, for example, sees education as a *signal* (see Spence[152]) for the inherent productivity of workers. Under strong versions of this model, education is seen as merely identifying students with particular attributes, acquired at birth or by virtue of family background, but does not itself produce or improve those attributes. Under weaker versions of the hypothesis, it is argued that employers use information about the average characteristics of groups of people to minimise the costs and risks associated with hiring. While an employer may not be able to be sure of the actual productivity of any particular applicant, they can choose on the basis of certain observed individual characteristics which they have found or believe to be correlated with productivity. These include things such as age, race and gender which cannot be changed. They also include *signals* like experience and education which are the result of individual choices, attributes and circumstances. In these models, therefore, the links between formal education and productivity are far weaker.

There are a number of variants of the screening hypothesis including the signalling model of Spence [152] and the jobs competition model of Thurow [155].

Spence's model assumes that workers know their own productivity but that firms are not able to identify which workers are the most productive. He also assumes that more able individuals can obtain an educational signal more cheaply than less able individuals. Under these assumptions he shows that profit maximising firms will pay wage premia to more educated workers even if education has no direct impact on productivity and that more able individuals will undertake more education because of these returns. The market equilibrium involves paying more educated workers higher pay even if this extra education has no effect of the worker's productivity.

Thurow argues that the labour market is characterised by *job competition* (that is jobs looking for people) rather than *wage competition* (people looking for jobs). In such a labour market, he argues, the function of education is not to confer skill and hence increase productivity. Rather it is to certify trainability and to confer upon workers a certain status by virtue of their formal education qualification. The distribution of jobs and income are a direct result of this education status. Thus he views employers as using education qualifications as a screening device to indicate the cost of training.

2.3 Education, Training and Life Cycle Earnings

2.3.1 Individuals' Education and Training Decisions

Whether one supports the human capital hypothesis or screening hypothesis, it is clear that individuals will invest in more education and training if they believe they will be better off (variously defined) by undertaking such courses. In the human capital model this is argued to be a result of the productivity enhancing role of education. In the screening model it arises because more able individuals have to undertake education in order to provide employers with a signal of their underlying ability. A number of theoretical models of individuals' education and training decisions have been proposed in the literature and these are reviewed below.

A simple model of educational choice

We begin by setting out a simple model where an individual will undertake an extra year of education if the present value of benefits is at least as large as the costs[2]. In most models the benefits are written in terms of earnings[3] and a person will undertake more education if

$$V = \sum_{t=s}^{T} \frac{(y_t^1 - y_t^0)}{(1+r)^t} + \sum_{t=0}^{s-1} \frac{(y_t^E - c_t^E) - y_t^0}{(1+r)^t} \geq 0 \tag{2.1}$$

or

$$V = \sum_{t=0}^{T} \frac{(y_t^1 - y_t^0)}{(1+r)^t} \geq 0 \tag{2.2}$$

where V is the *net present value* of investing in extra education, s is the time it will take to complete the schooling or college/university degree at time $t = 0$ when the decision is being made, y_t^E is income received while in education at time t, c_t^E are the non–wage costs associated with staying in education at time t, y_t^1 is the income received at time t if the individual undertakes education (where $y_t^1 = y_t^E - c_t^E$ when $t \leq s$), y_t^0 the income at time t if the individual does not undertake further education, T is the date of retirement, and r the individual's discount rate which is assumed to fixed and known. The individual's income can be written as

$$y_t^1 = p^1 w_t^1 + (1-p^1) u b_t \tag{2.3}$$

and

$$y_t^0 = p^0 w_t^0 + (1-p^0) u b_t \tag{2.4}$$

[2]This model is similar to that found in Ehrenberg and Smith[68].

[3]This assumption is not required in theoretical models but is usually implemented in econometric models because of the difficulty of observing the non–monetary benefits of education.

where $p_t^1$and p_t^0 are the probabilities of being employed at time t if the individual invests and does not invest in education respectively, w_t^1 and w_t^0 are the corresponding wages if they are in employment and ub_t the level of unemployment benefit at time t. The first term of equation (2.1) gives the yearly discounted difference in earnings between undertaking education and not undertaking education and the second term gives the total discounted cost of the education decision including foregone earnings. The *internal rate of return* for investing in education is given by the value of r, (r^*), which ensures that the present value of benefits equals costs, that is the left–hand side of equation (2.1) is zero. If the internal rate of return is greater than the market rate of interest, then the education is a worthwhile investment. Clearly the higher the internal rate of return, the better the investment will be viewed by the individual since it suggests that the investment is worthwhile even at high discount rates.

What are the implications of the simple model? The model suggests that people with high discount rates are, *ceteris paribus,* less likely to undertake education than more forward looking people with lower discount rates. It also suggests that it is far better for people to undertake their education investments earlier in life as this clearly gives them a longer time in which to reap the benefits of the extra education. We also see that the net benefits of education will decrease if the direct costs of education rise, other things being equal. The benefits of education will also decrease if the level of unemployment benefit increases assuming $p_t^0 < p_t^1$, that is if the probability of being employed is higher if an individual undertakes education. On the other hand the benefits of education will increase, *ceteris paribus*, if the earnings gap for educated people widens and/or if the income received by individuals undertaking education increases (for example through changes in part–time earnings or changes in the level of a student grant). Similarly, if the education gap widens in terms of either the wages received in work and/or the probability of being employed, then the net benefits of undertaking education will increase.

While it is doubtful that individual's actually undertake such a complex calculation as that suggested by equation (2.1), it seems reasonable to assume that factors like earnings and wage differentials, the present–orientedness of the individual making the decision, the direct costs of education, the level of unemployment benefit, the probability of getting a job as well as the level of student grants available to the individual may enter their decision of whether or not to invest in more education.

One obvious problem with this simple model is that future earnings can never be perfectly predicted. In a lot of models of the education investment decision, people argue that it is the average returns to different types of education which have an important influence on individual's human capital investment decisions. Others formulate the model in terms of *expected* returns which are, of course, subject to uncertainty.

The model presented above also ignores labour supply considerations and examines human capital investment decisions within a wealth rather than a utility maximising framework. A more rich model than the one presented above would allow the life cycle pattern of hours to vary and compare the utility derived from the individual's lifetime consumption when they do and do not invest in education. The model presented above also assumes individuals are unconstrained in the credit market. However, individuals undertaking education tend to be relatively young and therefore may not have collateral or sufficient credit histories upon which they can obtain loans to undertake education. The availability and terms of loans to finance education will clearly impinge on an individuals' investment decision.

It is also clear from studies like Butcher and Case[45] and Borjas [35] that factors other than earning differentials are also important in the human capital investment decision. These studies suggest that factors such as sibling sex composition and an individual's ethnic affiliation might also have important implications for human capital investment decisions and subsequent labour market outcomes. Other issues will also impinge on the individual's decision such as the supply of educational places, and the numbers of individuals making similar investments.

We now move on to look at some of the theoretical models which have been formulated in the literature to look at these issues. There is a large literature on the determinants of life cycle earnings and this has been comprehensively reviewed by people like Rosen[140] , Killingsworth [109] and Weiss [158]. In this section we review only a small selection of this literature, focusing on models which have direct applications in empirical work looking at the determinants of and returns to education and training. The first model we look at is a simple schooling model developed by Card [51] which draws on the early work of Becker [17].

The Card Model

Card [51] assumes that individuals choose schooling to maximize a utility function defined over average earnings per year ($\overline{y}$) and years of schooling (s). His utility function is given by

$$U(\overline{y}, s) = \ln \overline{y} - \varphi(s) \tag{2.5}$$

where $\varphi(s)$ is an increasing convex function[4]. The individual's opportunities are summarised by a function $\overline{y} = g(s)$, representing the level of earnings available at each level of education. The first order conditions for the optimal choice of schooling is given by

$$\frac{g'(s)}{g(s)} = \varphi'(s) \tag{2.6}$$

The optimal level of schooling is that which equates the marginal rate of return to schooling ($g'(s)/g(s)$) with the marginal cost ($\varphi'(s)$)[5]. Card

[4]As Card points out, the simplest form of this utility function assumes that the individual maximises the discounted present value of income, discounts the future at a constant rate r, and earns nothing while in school, i.e. $U(\overline{y}, s) = \ln \overline{y} - rs$.

[5]This assumes that $g(s)$ is log-concave.

assumes that both the marginal rate of return and marginal cost of schooling are *linear* functions with person specific intercepts and homogeneous slopes, that is

$$\frac{g'(s)}{g(s)} \equiv B_i(s) = b_i - k_1 s \tag{2.7}$$

and

$$\varphi'(s) \equiv R_i(s) = r_i + k_2 s \tag{2.8}$$

where $k_1 \geq 0$ and $k_1 \geq 0$. Thus the optimal levels of schooling are given by equating equations (2.7) and (2.8) giving

$$s^* = \frac{(b_i - r_i)}{k_1 + k_2} \tag{2.9}$$

where $B_i(s)$ and $R_i(s)$ are measured in units of percentage points per year. Thus in Card's model, schooling choices vary for two reasons. The first is because individuals have different returns to schooling, that is there is variation in b_i across individuals. The second is because individuals have higher or lower marginal rates of substitution between schooling and future earnings, that is there is variation in r_i across individuals. Card argues that variation in b_i corresponds to variation in "ability" whereas variation in r_i corresponds to variation in "access to funds" (family wealth) or "tastes for schooling".

The attraction of Card's model is that it can easily be used to derive an earnings function which can be used to estimate the returns to schooling. Moreover, his model offers interesting interpretations of the estimates of these returns to schooling. This is considered more fully below. Card's model, however, makes a number of simplifying assumptions. He assumes that utility is a function of average earnings per year. He therefore assumes that fluctuations in average earnings over the life cycle do not impinge on individual's schooling decisions. In his model he treats labour supply as fixed or known, since utility is only a function of average income and schooling. Finally the model only looks at schooling decisions, it does not consider human capital investment over the entire life cycle. This final issue was explored in more detail by Ben-Porath [23].

The Ben-Porath Model

Ben-Porath's [23] 1967 article on the production of human capital was the first serious attempt to formulate a model of optimal rates of human capital investment over the earnings cycle. In his model, a person's stock of human capital at time t, K_t, can be used to generate income or to generate more human capital. New human capital is produced from current capital according to the strictly concave individual human capital production function

$$q_t = a(\tau_t K_t)^b \tag{2.10}$$

where $0 \leq \tau_t \leq 1$ is the proportion of the human capital stock K_t diverted from earnings to generate more human capital, $0 < b < 1$ is an "ability" parameter, and $a > 0$ a constant[6]. Income at time t is given by

$$y_t = \omega(1 - \tau_t)K_t \tag{2.11}$$

where $\omega > 0$ is the wage per unit of human capital. This wage rate is assumed to be constant over the life cycle and independent of the stock of human capital. The rate of change of the human capital stock is given by

$$\frac{dK_t}{dt} = q_t - \delta K_t \tag{2.12}$$

[6]Ben-Porath actually allowed the flow of new human capital, q_t, to also arise from purchased inputs D_t according to the production function: $q_t = a(\tau_t K_t)^{b_1} D_t^{b_2}$ where $b_1, b_2 > 0$ and $b_1 + b_2 < 1$.

where δ is the human capital depreciation rate. The investment cost of human capital is given by foregone earnings[7]

$$C_t = \omega \tau_t K_t \tag{2.13}$$

An individuals optimal human capital investment path is the one which maximizes the present value of the individual's income stream

$$V = \int_0^T y_t e^{-rt} dt \tag{2.14}$$

subject to equations (2.10), (2.11),(2.12) and (2.13)[8].

The marginal cost of producing a unit of human capital at t is obtained by differentiating (2.13) subject to (2.10) and is given by[9]

$$\frac{dC_t}{dq_t} = \frac{\omega}{a^{1/b} b} q_t^{(1-b)/b} \tag{2.15}$$

From equation (2.15) we see that marginal cost is increasing with respect to q_t but is constant with respect to t. The marginal cost curve becomes vertical, however, when $\tau_t = 1$. The benefit of an extra unit of human capital is the present value of the stream of future wages ω, less depreciation which that unit will bring. The present value of this marginal benefit is given by

$$\frac{dB_t}{dq_t} = \omega \int_t^T e^{-(r+\delta)v} dv = \frac{\omega}{(r+\delta)} \left(e^{-(r+\delta)t} - e^{-(r+\delta)T} \right) \tag{2.16}$$

[7]Because we are assuming that the flow of human capital produced only arises from existing human capital and not from purchased inputs, there are no direct costs of education. Again, in Ben-Porath's original model he allowed for the direct costs of purchasing goods and services and therefore investment costs were given by: $C_t = \omega \tau_t K_t + P_d D_t$ where P_d is the price of purchased inputs D_t.

[8]This can be done directly using optimal control methods, or by equating the marginal costs with the marginal benefits of producing a unit of human capital at t.

[9]In Ben-Porath's full model we have:

$$\frac{dC_t}{dq_t} = \frac{\omega}{ab_1} \left(\frac{b_1 P_d}{b_2 \omega} \right)^{b_2/(b_1+b_2)} \left(\frac{q_t}{a} \right)^{(1-b_1-b_2)/(b_1+b_2)}$$

which is equivalent to equation (2.15) if we set $b_2 = 0$.

and is approximately equal to $\omega/(r+\delta)$ when a person is young (i.e. $T-t$ large) and is close to zero by the time a person approaches retirement at $t=T$. From (2.16) we see that this marginal benefit is constant with respect to q_t but is decreasing with respect to t.

During the early years of a persons life (during full-time schooling) the entire stock of human capital is used to produce more human capital (i.e. $\tau_t = 1$) and income is zero. At this stage individuals are not able to equate marginal costs and benefits since they are on the vertical region of the marginal cost curve. This implies that individuals would rather invest more than they do, but cannot because of limited time resources. Hence at this time in the life cycle, marginal benefits are greater than marginal costs. During the middle years of an individuals life as marginal benefits decline, the human capital stock is used both to produce more human capital and to generate income. At this stage optimal investment is determined by equating the marginal costs and marginal benefits from investment. Equating (2.15) with (2.16) we get[10]

$$q_t = \left\{ \frac{a^{\frac{1}{1-b}} b}{r+\delta} \left[e^{-(r+\delta)t} - e^{-(r+\delta)T} \right] \right\}^{b/(1-b)} \tag{2.17}$$

This suggests that human capital investment decisions vary across individuals because of a number of reasons. Firstly human capital output, q_t, and hence earnings, is smaller the higher the discount rate r and rate of depreciation of human capital δ. Individuals facing higher discount rates and/or depreciation rates will invest less, accumulate less capital and hence have lower earnings growth than individuals with lower discount rates and/or depreciation rates. We also see that human capital output increases with ability. This arises

[10]In Ben-Porath's full model the solution is given by

$$q_t = \left(\frac{b_2 \omega}{b_1 P_d} \right)^{b_2/(1-b_1-b_2)} \left\{ \frac{a^{\frac{1}{1-b}} b_1}{r+\delta} \left[e^{-(r+\delta)t} - e^{-(r+\delta)T} \right] \right\}^{(b_1+b_2)/(1-b_1-b_2)}$$

which is equivalent to equation (2.17) if we set $b_2 = 0$.

because having more ability lowers the marginal cost of acquiring additional human capital. Finally the equation tells us that the production of human capital declines with age (i.e. as t increases) over this period. Eventually a point is reached where additions are not sufficient to offset depreciation, that is $q_t < \delta K_t$, and the human capital stock declines thereafter and falls to zero at retirement $(t = T)$. At this point earnings peak and thereafter decline.

The model also allows one to make a distinction between potential earnings, E_t, and observed earnings, y_t, given in equation (2.11). Potential earnings, are defined as the most an individual aged t could earn if they spent all their time working, that is

$$E_t = \omega K_t = y_t + C_t \tag{2.18}$$

From equation (2.18) it is easy to show that the two wage profiles have different peaks. Net or observed earnings continue to rise after capacity earnings have peaked. From equation (2.18) we see that the peak of capacity earnings is reached when

$$\frac{dE_t}{dt} = 0 = \frac{dy_t}{dt} + \frac{dC_t}{dt} \tag{2.19}$$

At the peak of E_t, $dy_t/dt > 0$ since $dC_t/dt < 0$. Hence the model implies that actual earnings are always lower, change faster and peak at a later age than capacity earnings.

What are the implications of this model? The model suggests that human capital stocks are determined by individuals rationally deciding the proportion of time devoted to human capital investment through their life. The model is consistent with observed life cycle earnings. There is an initial period of no earnings followed by a period where earnings rise at a decreasing rate before eventually falling. The model also suggests that education and on-the-job training are complements. As with Card's model, it can be used to derive an empirical formulation of the earnings function which can be used to estimate the returns to schooling and on-the-job training. This is discussed in more detail below.

The Ben-Porath model also makes a number of simplifying assumptions. First of all it assumes that future benefits are known with certainty and that the retirement age is also known with certainty. One also might imagine that later human capital investments could be more costly if the opportunity costs of time devoted to investments increase. The model, however, assumes that the marginal cost of investments is fixed over the life cycle. This is because it assumes that the productivity in learning grows as fast as productivity in earnings. This "neutrality hypothesis" can be easily relaxed. Another simplifying assumption of the model is the two-way allocation of time between learning and earning. Time spent in consumption or leisure is not considered or assumed fixed. Blinder and Weiss [29] and Heckman [96] have extended the Ben-Porath model to allow three way choices. Heckman also avoids the need for the schooling period to be associated with a corner solution in terms of hours as is assumed in the Ben-Porath model. He instead defines the schooling period as one in which hours of work are low or in which there are high levels of purchased inputs[11]. Heckman [96] finds, however, that the implications of the Ben-Porath model stay largely in tact.

The models considered so far also assume that human capital decisions are made with perfect foresight about either the stream of future income (Ben-Porath) or average income (Card) over the life cycle. Investment in human capital, however, is widely recognised to be subject to risk and this uncertainty will affect individual human capital investment decisions. The issue of uncertainty was first considered by Levhari and Weiss [114] and has subsequently been extended by Snow and Warren [149]. Snow and Warren show that if investment in human capital is not an inferior activity, then the effect of an increase in earnings uncertainty on human capital investment

[11]That is high levels of D_t in the full Ben-Porath model.

is indeterminate. In their model they allow future labour supply to be a choice variable. Kodde's [110] empirical work on this question using a sample of Dutch high school students suggests that increased earnings uncertainty increased human capital investment.

Families and Investment in Human Capital

It has also long been recognised that families play an important role in determining the future success of children. As we saw in Card's model, investment in schooling is determined by "ability" and "access to funds" or "tastes for schooling" and it is clear that the family plays a potentially crucial role in determining both an individual's ability and opportunities. Economic models which focus on the effect of families, include those of Behrman, Pollack and Taubman [21], Behrman and Taubman [22], Becker [19] and Griliches [83]. These models suggest that under certain circumstances, a child's education can depend on factors such as their gender, the size of their family, parental interest in the child's education, the child's birth order, and/or the sex composition of their sibship.

For instance Becker [19] assumes that households maximise utility functions which are functions of child "quality", consumption, and the number of children. If parent's face no borrowing constraints, then investment in human capital will continue until the marginal return to education for each child is equal to the market rate of interest. In richer families therefore, investment in human capital depends only on a child's own characteristics or quality, unless parents have an aversion to earnings inequality among their children.

For families facing borrowing constraints, the situation is different and they have a conflict between equity and efficiency. They will only invest more in more able children if efficiency outweighs equity considerations. Hence the relation between ability and education will tend be weaker in poorer families and factors like family size, composition, parental interest and the child's position in the family may impact on how human capital investment decisions are made by parents.

Research in other disciplines, also predicts that family size, composition, parental interest and factors like birth order, may effect educational outcomes. The literature on birth order is reviewed by Behrman and Taubman[22] and there are clearly competing theories as to whether earlier or later children should have better education outcomes. The confluence model of Zajonc [163] suggests that earlier born children should do better than later born children because: the average intelligence of families declines as more children are born which affects the average family environment; and because older children learn more from teaching younger children than younger children actually gain from such instruction. Other theories supporting this hypothesis argue that the interest parents show in a child's education is a crucial factor in educational attainment, and this tends to decline as the family grows. If however, parents improve their child rearing skills as they have more children, later born children may do better.

Butcher and Case [45] review the literature on composition of sibships. Again, there are a number of competing theories on how the sex composition of an individual's siblings may affect their educational outcomes. These offer reasons why, for example, women may do better if they only have brothers or only have sisters. For example, sons may have a positive effect on a daughter's educational outcome if parents have educational ambitions for their sons and use the same frame of reference for a subsequent daughter. If, however, they have another daughter, this frame of reference may change. On the other hand, if parents face borrowing constraints, and boys have a higher marginal return to education (because of stronger labour market attachment), then the presence of sons could reduce girls educational attachment. As Butcher and Case point out, a girl with only sisters would receive more education than a girl with brothers if this effect was operating.

It is clear from the preceding discussion that the exact role families play in determining educational outcomes remains an empirical question. We will look at this issue in detail in this thesis. The data we use has information on family background variables including family size and birth order. The NCDS data also has detailed information on the composition of the child's sibship as well as on how the child's teacher perceived the interest shown by the parents in their child's education at an early age.

2.3.2 Education, Training and Life Cycle Earnings Functions

In this section we look at how we can use the various models discussed above to obtain earnings functions which can be used in empirical applications.

Card's Earnings Function

In Cards formulation, we can derive and equation for the log earnings of individual i by integrating equation (2.7) giving

$$\ln y_i = a + b_i s_i - \frac{1}{2} k_1 s_i^2 \tag{2.20}$$

where a is a constant which could be allowed to vary across individuals. In Card's model equations (2.9) and (2.20) determine the joint distribution of earnings and schooling.

Mincers Human Capital Earnings Functions

Mincer [128] used the Ben-Porath model (and variations of it) to derive empirical earnings function and these earnings function are generally referred to as "human capital earnings functions" in the literature. In the Ben-Porath model, potential earnings in period t are given by potential earnings in period $t-1$ plus the gross returns on human capital investments undertaken in period $t-1$ less depreciation

$$E_t = E_{t-1} + rC_{t-1} - \delta E_{t-1} \tag{2.21}$$

which can be re-written as

$$\frac{E_t}{E_{t-1}} = 1 + r\frac{C_{t-1}}{E_{t-1}} - \delta = 1 + r\left(\frac{C_{t-1}}{E_{t-1}} - \frac{\delta}{r}\right) \tag{2.22}$$

The cost of human capital investment, however is rarely observed in empirical data. Mincer therefore relies on creating a measure of the time involved in the investment, "the time equivalent investment", which is given by

$$\tau_t = \frac{C_t}{E_t} = \tau_t^* + \frac{\delta}{r} \tag{2.23}$$

where τ_t and τ_t^* are the gross and net investment fractions respectively. The gross ratio represents the fraction of potential earnings the individual forgoes to accumulate extra human capital[12]. Substituting for C_t in equation (2.21) using equation (2.23) we get

$$E_t = E_{t-1}(1 + r\tau_{t-1} - \delta) \tag{2.24}$$

which by recursion gives us

$$E_t = E_0 \prod_{t=0}^{t-1}(1 + r\tau_t - \delta) \tag{2.25}$$

Taking logarithms of both sides of equation (2.25) we get

$$\ln E_t = \ln E_0 + \sum_{t=0}^{t-1} \ln(1 + r\tau_t - \delta) = \ln E_0 + \sum_{t=0}^{t-1}(r\tau_t - \delta) \tag{2.26}$$

where we have used the fact that $\ln(1 + r\tau_t - \delta) \cong (r\tau_t - \delta)$ when $(r\tau_t - \delta)$ is small. However, in the Ben-Porath model, $\tau_t = 1$ while a person is undertaking schooling. After schooling is completed, τ_t declines with time and equals zero at retirement. If we distinguish between the full-time schooling period and the post-schooling period we can re-write equation (2.26) as

$$\ln E_t = \ln E_0 + (r - \delta)s + \sum_{t=s+1}^{t-1}(r\tau_t - \delta) \tag{2.27}$$

[12]This again assumes there are not direct costs associated with the investment.

where s is the number of years of schooling, and $\sum_{t=0}^{s} \tau_t = s$ since $\tau_t = 1$ for $t \leq s$. But from equations (2.18) and (2.23) we have $y_t = E_t(1 - \tau_t)$ and substituting this into equation (2.28) we get

$$\ln y_t = \ln E_0 + \ln(1 - \tau_t) + (r - \delta)s + \sum_{t=s+1}^{t-1} (r\tau_t - \delta) \tag{2.28}$$

Mincer [128, pp. 83–88] examines the implications using a number of assumptions about the profile of the time-equivalent investment ratio τ_t. He defines τ_0 as the investment ratio during the initial period of work experience and N as the total period of positive net investment He shows, for example, that if the investment ratio is assumed to decline linearly with experience on the job $(t - s)$ [13] according to the relationship

$$\tau_t = \tau_0 - \frac{\tau_0}{N}(t - s) \tag{2.29}$$

then the gross and net earnings functions become becomes parabolic with respect to experience and is given by

$$\begin{aligned} \ln y_t &= \ln E_0 + \ln(1 - \tau_0 - \frac{\tau_0}{N}(t - s)) + (r - \delta)s \\ &\quad + (r\tau_0 - \delta)(t - s) - \frac{r\tau_0}{2N}(t - s)^2 \end{aligned} \tag{2.30}$$

This is the well know human capital earnings function which can be estimated by

$$\ln y_i = \beta_0 + \beta_1 s_i + \beta_2 \exp_i + \beta_3 \exp_i^2 + u_i \tag{2.31}$$

where $\exp_i = t - s_i$ for individual i. The earnings function given by equation (2.30) assumes that all workers have the same own rate of return to the investment and that the fraction of earnings invested in education is identical

[13] He defines work experience as age minus years of schooling minus the age at the beginning of schooling. In our model $t = 0$ at the time a person begins school, therefore experience is given by $t - s$.

for workers with the same experience, that is r and τ_t are identical for all individuals. Mincer suggests including schooling squared and an interaction term of schooling times experience as extra regressors so that workers can differ in these characteristics across schooling groups. Thus a more general earnings function is of the form

$$\ln y_i = \beta_0 + \beta_1 s_i + \beta_2 \exp_i + \beta_3 \exp_i^2 + \beta_4 s_i^2 + \beta_5 s_i \exp_i + u_i \tag{2.32}$$

The earnings function given by equation (2.30) also suggests that a high on-the-job training investment ratio during the initial period of work experience (τ_0) is associated with lower initial earnings but higher earnings growth, given E_0 and r.

2.3.3 Education and Training as a Social Investment

In the preceding discussion we have focused solely on the private returns to investments in education and training by individuals. However, government expenditure on formal education in both schools and post–school educational institutions as well as on work related training schemes is substantial. The justification for government funding of education and training is based on the idea that education and training does more than provide private returns to the individuals and employers involved. Education and training is also seen to provide important social returns. Part of the justification for this public spending is in terms of the important cultural and social role education plays in society. But equally important is the view that education and training plays a crucial role in the overall productivity and general prosperity of the economy.

The private return to education is generally estimated assuming that the only cost of education is foregone earnings and that most of the direct costs of education are publicly subsidised. Earnings are taken to be net of taxes, though if the tax system is proportional then the use of pre- or post- tax earnings does not affect the rate of return. The social return to education includes the direct cost of education and its effect on national productivity (usually proxied by pre-tax earnings). Psacharopoulos [137] argues that most of the difference between private and social returns reflect the direct costs of schooling. If education is predominantly a screening device and does not impact on productivity, then the social rates of return to education will be well below the private returns and could even be negative.

The argument that education plays an important role in the productivity of the individual is clearly underpinned by *human capital theory.* If, however, education and training serve primarily as *screening* devices for employers then the link between education and productivity is far weaker. Whether education is purely a screening device or increases productivity is not an important questions for individuals' education choice. In both these models, individuals will invest in more education and training if they believe they will be better off by undertaking such courses. These issues, are, however, clearly important when looking at the role of government in subsidising education and training and the validity or otherwise of these two views has important implications for public policy. However, differentiating between them is quite difficult. In order to test the competing theories we need to separate the effect of education from underlying ability. It is very rare to have good enough data to separate such effects. The NCDS data used in this thesis has information on both educational outcomes and the results of ability tests undertaken when the individual was very young. This issue is explored more fully in Chapter 5.

2.4 Estimating the Returns to Education and Training

There are a number of problems associated with estimating earnings equations like those derived in the previous section. These primarily relate to the fact that schooling and training are not necessarily exogenous, and if this is true, then OLS estimation of these earnings functions will yield biased estimates of the returns to education and training. There is a large econometric literature devoted to this issue and this is partially reviewed below. We first look at the issues involved in estimating the returns to education. We then move on to look at methods for estimating the returns to training. While a lot of the issues in estimating the returns to education and training overlap, there are important differences. This is largely a result of the fact that when estimating the returns to training we quite often observe wages both before and after the training event whereas this is generally not true for schooling. This has important implications for the types of estimation procedures that can be used.

2.4.1 Estimating the Returns to Education

The conventional approach to estimating the returns to schooling involves using a two equation system of the form

$$y_i = s_i\beta_1 + X_i'\beta_2 + u_i \tag{2.33}$$

$$s_i = Z_i'\gamma + v_i \tag{2.34}$$

where s_i is years of schooling (full-time education), y_i is a measure of log earnings, X_i and Z_i are vectors of observed individual characteristics, β_1 is the return to schooling, u_i and v_i are a pair of residuals, and $E(X_iu_i) = E(Z_iv_i) = 0$ (see Card [51, pp 5–6]). OLS estimation of equation (2.33) gives rise to a unbiased estimate of β_1 if u_i and v_i are uncorrelated, that is if s_i is exogenous ($E(s_iu_i) = 0$). If this does not hold, then alternative estimation procedures need to be used and these are reviewed below.

Proxying Unobserved Fixed Effects

One approach which has been used in the literature to obtain consistent estimates of the returns to schooling is to proxy the correlated unobserved fixed effect. In the returns to schooling literature these studies have tended to concentrate on omitted ability bias and have used observed measures of ability such as IQ tests and other ability tests to proxy unobserved ability[14]. Assume that the residuals in equations (2.33) can be decomposed as

$$u_i = A_i + \eta_i \tag{2.35}$$

where the correlation between s_i and u_i arises because of correlation between A_i and u_i and by construction $E(\eta_i v_i) = E(\eta_i s_i) = 0$. In this formulation, A_i represents time invariant unobserved ability which is correlated with both schooling and earnings. Both the signalling and human capital models presented above, suggest that education and ability are positively correlated and estimation procedures which do not take this into account will therefore over-estimate the true returns to education. Suppose we can model ability as

$$E(A_i|P_i, s_i, X_i) = P_i'\pi \tag{2.36}$$

where P_i are observable variables which are thought to proxy unobserved ability (for example results of ability tests and family characteristics). Then conditional on these variables, $A_i - E(A_i|P_i, s_i, X_i)$ will be uncorrelated with the schooling variable which appears in the wage equation. Thus we can instead estimate the following equation consistently by OLS

$$y_i = s_i\beta_1 + X_i'\beta_2 + P_i'\pi + \widetilde{u}_i \tag{2.37}$$

where $\widetilde{u}_i = A_i - E(A_i|P_i, s_i, X_i) + \eta_i$ and $E(\widetilde{u}_i, s_i) = 0$. The ability to proxy the unobserved fixed effect is clearly going to depend on the quality of the data being used. The problem with this approach, as pointed out by Welch [160] and Griliches [82], is that the more variables we include in our earnings equation to overcome biases related to missing ability variables, the

[14]The approach has also been used to proxy the "family effect" in twin and sibling studies. We look at this in more detail below.

more we raise problems of biases arising from measurement error. The issue of measurement error is examined in more detail below for the case where schooling is measured with error. The problems associated with measuring both schooling and ability with error are addressed in Chapter 5.

Instrumental Variables Approaches

Instrumental variable approaches identify a set of exogenous variables that affect the education decision, but not earnings controlling for education. These variables can then be used to correct for the endogeneity of education through instrumental variable techniques. In order for the model to be identified we need variables in our Z_i can be legitimately be left out of the earnings equation (2.33). Thus we have $Z_i' = (X_i', W_i')$ where W_i is a vector containing at least one variable for identification. An alternative way of carrying out this IV estimation which provides a direct test of the exogeneity of schooling is to decompose the error term in equation (2.33) as follows

$$u_i = \alpha v_i + \eta_i \tag{2.38}$$

where η_i and v_i are uncorrelated by construction. If $\alpha = 0$ then u_i and v_i are uncorrelated by definition and OLS estimation of equation (2.33) provides us with a consistent estimate of β_1. To see if this is the case we estimate equation (2.34) by OLS and calculate

$$\widehat{v}_i = s_i - Z_i'\widehat{\gamma} \tag{2.39}$$

We can then estimate the following model

$$y_i = s_i\beta_1 + X_i'\beta_2 + \alpha\widehat{v}_i + \eta_i \tag{2.40}$$

by OLS and this will provide a consistent estimate of β_1, since conditional on v_i, X_i and s_i are uncorrelated with η_i. Smith and Blundell [148] show that a Hausman [94] type test of the exogeneity of schooling is obtained by testing whether $\alpha = 0$ in equation (2.44). When estimating an equation of this form, the standard errors of the estimates have to be corrected to take account of the fact that the regression equation contains a generated regressor.[15].

A variant of the instrumental variables technique which has been used in the schooling literature, argues that schooling is not a continuous variable since in most data sets there will be a considerable proportion at the minimum level of s and it also seems reasonable to assume that schooling decisions consist of a number of discrete jumps due to rules governing completion of education. Other studies instead of using years of education, have a series of dummy variables identifying the individual's highest education qualification which often have a distinct ordering. Studies like Gregory and Vella [156] and Harmon and Walker [90] therefore assume that equation (2.34) is replaced with a latent model of the form

$$s_i^* = Z_i'\gamma + v_i \tag{2.41}$$

where

$$s_{ij} = 1 \text{ if } \mu_{j-1} < s_i^* \leq \mu_j \tag{2.42}$$

and where $j = 0, 1, 2, 3...$ and $\mu_{j-1} < \mu_j$. The schooling equation is now estimated as an ordered probit. Following Heckman (1979) we can then construct the selection adjustment term as

$$\widehat{\lambda}_i = \frac{\phi(\widehat{\mu}_j - Z_i'\widehat{\gamma}) - \phi(\widehat{\mu}_{j+1} - Z_i'\widehat{\gamma})}{\Phi(\widehat{\mu}_{j+1} - Z_i'\widehat{\gamma}) - \Phi(\widehat{\mu}_j - Z_i'\widehat{\gamma})} \tag{2.43}$$

where the $\widehat{\mu}_j$'s and $\widehat{\gamma}$ are the estimates obtained from the ordered probit maximum likelihood procedure, and $\phi(.)$ and $\Phi(.)$ are the normal probability distribution and normal cumulative distribution functions respectively. We can then estimate the following equation

$$y_i = s_i'\beta_1 + X_i'\beta_2 + \varphi\widehat{\lambda}_i + \eta_i \tag{2.44}$$

[15]This issue is discussed more fully in Pagan [135] and Arellano and Meghir[4].

by OLS since conditional on λ_i, X_i and s_i[16] are uncorrelated with η_i. If schooling is exogenous then $\varphi = 0$ in equation (2.44). As with the modified instrumental variable technique discussed above, the standard errors of the estimates have to be corrected to take account of the fact that the regression equation contains a generated regressor.

Twin and Sibling Data

An alternative to instrumental variables approaches is to use data on twins or siblings to eliminate endogeneity bias by exploiting the differences between twins and/or siblings levels of schooling and earnings. This was the approach taken by Ashenfelter and Zimmerman [12] using data on fathers, sons, and brothers; and Ashenfelter and Krueger[11] using data on identical twins. Ashenfelter and Krueger [11] denote by y_{1i} and y_{2i} the logarithm of the wage rate of the first and second twins in the ith pair. They divide their explanatory variables into those that vary by family but not between twins X_{fi} and those which vary across twins, X_{1i} and X_{2i}. Clearly schooling s_i will also vary across twins, s_{1i} and s_{2i}. Similarly they assume that there is an unobservable component that varies by family, f_i, and unobservable individual components, $u_{1i} = f_i + \eta_{1i}$ and $u_{2i} = f_i + \eta_{2i}$. This implies that

$$y_{1i} = s_{1i}\beta_1 + X'_{1i}\beta_2 + X'_{fi}\beta_3 + f_i + \eta_{1i} \tag{2.45}$$

$$y_{2i} = s_{2i}\beta_1 + X'_{2i}\beta_2 + X'_{fi}\beta_3 + f_i + \eta_{2i} \tag{2.46}$$

where it is assumed that the equations are identical for the two twins. They assume that the correlation between this family effect and the observables for each twin are the same and can be proxied by

$$f_i = X'_{1i}\psi + X'_{2i}\psi + \theta s_{1i} + \theta s_{2i} + X'_{fi}\delta + \mu_i \tag{2.47}$$

[16] In this formulation s_i is either years of education, or a vector of dummy variables identifying the individual's highest educational outcome, i.e. $s_i = (s_{i1}, s_{i2}, ...s_{ij})$.

where μ_i is uncorrelated with all the right hand side variables in equation (2.47). The coefficients ψ and θ measure the "selection effect" relating earnings and the observables, while the coefficients $\beta_1$and β_2 measure the selection corrected or the structural effect of the observables on earnings. Twin and/or sibling data therefore makes it possible to measure the selection effect of the rate of return to schooling (θ), and the selection corrected return to schooling (β_1). By substituting equation (2.47) into equations (2.46) and (2.45) we get the reduced form for the model

$$y_{1i} = (\beta_1+\theta)s_{1i}+\theta s_{2i}+X_{1i}'(\beta_2+\psi)+X_{2i}'\psi+X_{fi}'(\beta_3+\delta)+\mu_i+\eta_{1i} \quad (2.48)$$

$$y_{2i} = \theta s_{1i}+(\beta_1+\theta)s_{2i}+X_{1i}'\psi+X_{2i}'(\beta_2+\psi)+X_{fi}'(\beta_3+\delta)+\mu_i+\eta_{2i} \quad (2.49)$$

which can be estimated by OLS or GLS. GLS is optimal in this framework because of the cross equation restrictions on the coefficients and because it also provided the correct standard errors for the estimated coefficients. This framework suggests that both twin's education levels (and any other variable that varies by twins) may enter into both wage equations because of the correlations between the family effect and schooling levels. In this setup, the coefficients on the variables that differ by siblings (β_1 and β_2) are identified, however, the coefficients on the variables that only differ across families (β_3) are not identified. The difference between equations (2.46) and (2.45) (or (2.48) and (2.49)) is given by

$$y_{1i} - y_{2i} = (s_{1i} - s_{2i})\beta_1 + (X_{1i} - X_{2i})'\beta_2 + (\eta_{1i} - \eta_{2i}) \quad (2.50)$$

where in this formulation the family effect f_i has been eliminated. OLS estimation of equation (2.50) gives the traditional "fixed effects" estimator. Hence we have two approaches with this sort of data. We can proxy the family effect and use equations (2.48) and (2.49) to estimated the selection effect explicitly and then subtract this to obtain the selection corrected estimates of the returns to schooling. Alternatively we can eliminate the selection term by differencing and estimate the selection corrected return to schooling for OLS estimation of equation (2.50). The fixed effect estimator has the disadvantage of introducing far greater measurement error bias as shown by Griliches [83]. We discuss the problem of measurement error in more detail below.

Other Fixed Effects Estimators

Another approach to the endogeneity problem is to treat the unobserved correlated effect as fixed and use individual panel data to eliminate this fixed effect. This approach, like the approach used in the twins and siblings studies is open to measurement error problems. Also its applicability for studies looking at the returns to schooling is quite limited because we typically only observed data on earnings after individuals have completed all their schooling. This means that schooling as well as the unobserved fixed effect is eliminated when we take first differences in earnings. This method is much more applicable in studies looking at the returns to training since wages are generally observed both before and after the training takes place. We therefore consider this method in more detail below.

Biases Caused by Measurement Error

Suppose that our schooling variable is measured with error so that

$$s_i = s_i^* + m \tag{2.51}$$

where s_i^* is the true levels of education and m is the measurement error which is assumed to be uncorrelated with the true level of schooling. Under these assumptions OLS estimation of equation (2.33) (ignoring selection effects and assuming a univariate regression) will yield inconsistent estimates of the returns to schooling with

$$p\lim \widehat{\beta}_1^{OLS} = \beta_1^{OLS}\left[1 - \frac{\sigma_m^2}{(\sigma_m^2 + \sigma_{s^*}^2)}\right] = \beta_1^{OLS}\Psi \tag{2.52}$$

where $\beta_1^{OLS}$is the population coefficient if schooling were perfectly measured, $\sigma_{s^*}^2$ is the variance in true schooling levels and σ_m^2 is the variance in measurement error and Ψ the "reliability ratio" in the level of schooling. Thus estimates that do not take into account possible measurement error will underestimate the returns to schooling. Ashenfelter and Krueger [11] suggest that the extent of this downward bias in their study is around 10 per cent, that is they estimate a reliance ratio of 0.90. In the presence of selection effects as we have seen above, OLS estimation of equation (2.33) will be biased even if education is perfectly measured.

If one uses fixed effects methods to eliminate this selection effect, then one does so at the expense of introducing far greater measurement error as shown by Griliches [83]. For example, the probability limit of the fixed effects estimator of equation (2.50) (again ignoring other covariates) is given by

$$p\lim \widehat{\beta}_1^{FE} = \beta_1^{FE}\left[1 - \frac{\sigma_m^2}{(\sigma_m^2 + \sigma_{s^*}^2)(1-\rho_s)}\right] = \beta_1^{FE}\Psi^* \tag{2.53}$$

where ρ_s is the correlation between the measured schooling levels of the twins and β_1^{FE} is the population fixed-effects estimator that would have been obtained in the absence of measurement error and Ψ^* the fixed effect "reliability ratio". As Ashenfelter and Krueger [11] point out, if the correlation between the twins self-reported schooling is 0.66, then assuming a reliance ratio of 0.90, the fixed effects estimator would be biased downwards by around 30 per cent compared to its value in the absence of measurement error.

OLS estimation in the presence of measurement error will result in biased estimates of the returns to education. If, however, we have a set of instruments which are correlated with the true measure of education and uncorrelated with the measurement error, then we can once again rely on instrumental variable techniques. This means that measurement error should not affect the estimated returns to education from a valid instrumental variables procedure. The difference between OLS and IV estimates will therefore reflect a combination of the effects of measurement error and the endogeneity of schooling. The presence of measurement error in schooling will, however, result in downward bias in OLS and fixed effects estimations procedures. Finding appropriate instruments for within family fixed effects estimation procedures will often be difficult, as potential instruments such as family background variables will no longer be available. Approaches which have been used in the literature are discussed in more detail below.

In the discussion so far, we have assumed that schooling is the only variable which is measured with error. If other variables in the wage equation are also measured with error, then Welch [160] shows that the OLS estimate of the return to schooling may no longer result in an overestimate of the return to education. We look at this issue in more detail in Chapter 5 when we look at the issue of omitted ability bias.

Which Way do the Biases Go and Why?

Under what circumstances, if any, do OLS, instrumental variables and/or fixed effects estimators give unbiased estimates of the average marginal return to education?

To answer this question we return to Card's [51] schooling model discussed above. If we ignore other covariates in the earnings equation, the theoretical regression coefficient β_1 of the regression of log earnings on schooling is given by

$$\beta_1 = cov(y_i, s_i)/var(s_i) = E(y_i \cdot (s_i - \overline{s}))/var(s_i) \tag{2.54}$$

where $\overline{s}$ is the mean years of schooling. Using equations(2.9) and (2.20), in terms of Card's model, the first term in this expression is given by

$$E(y_i \cdot (s_i - \overline{s})) = E\left[b_i \frac{(b_i - r_i)}{k} \frac{(b_i - \overline{b}) - (r_i - \overline{r})}{k} - \frac{1}{2} k_1 s_i^2 (s_i - \overline{s}) \right] \tag{2.55}$$

where $\overline{b}$ and $\overline{r}$ are the expectations of b_i and r_i respectively and the second term is given by

$$var(s_i) = \frac{1}{k^2}\left[\sigma_b^2 + \sigma_r^2 - 2\sigma_{br}\right] \tag{2.56}$$

where σ_b^2 and σ_r^2 are the variances in b_i and r_i respectively, and σ_{br} their covariance[17]. Card then assumes that b_i and r_i are symmetrically distributed, which implies that the population regression coefficient is a weighted average of $\bar{b}$ and $\bar{r}$

$$\beta_1 = (1-\alpha)\bar{b} + \alpha\bar{r} \tag{2.57}$$

where

$$\alpha = \frac{k_1}{k} - \lambda \tag{2.58}$$

and

$$\lambda = \frac{\sigma_b^2 - \sigma_{br}}{(\sigma_b^2 - \sigma_{br}) + (\sigma_r^2 - \sigma_{br})} \tag{2.59}$$

He interprets λ as the fraction[18] of the variance of schooling attributable to variation in ability as opposed to variation in discount rate. If we assume that individuals maximize the discounted present value of earnings at a fixed individual discount rate (i.e. $k_2 = 0$ in equation (2.8)), then $\alpha = 1 - \lambda$, and the conventionally estimated return to schooling is given by

$$\beta_1 = \lambda\bar{b} + (1-\lambda)\bar{r} \tag{2.60}$$

If the marginal discount rate is increasing with respect to schooling, then in order for α to be inside the $[0,1]$ interval we require

$$k_1 \geq \lambda(k_1 + k_2) \tag{2.61}$$

which Card shows in equivalent to requiring that the predicted marginal return to schooling (given observed schooling) to be decreasing in s_i. This condition means that individuals with higher levels of schooling must have lower marginal returns to schooling, on average. This suggests that there may be no unique causal effect of education if, for example, different individuals

[17]See Card [51, pp 15–18]

[18]This interpretation is always correct if $\sigma_{br} = 0$. If this doesn't hold, then λ will only be bounded by 0 and 1 as long as $\sigma_{br} < \sigma_b^2$.

have different returns to education at the same level of education, or if each individual's return to schooling is strictly decreasing.

The expected increase in earnings of undertaking an extra year of schooling is given by the average marginal return to education $\overline{B} = E(B_i)$, however, for any particular individual it may well be below or above this average marginal return. From equation (2.7), the average marginal return to education is given by

$$\overline{B} = \bar{b} - k_1 \bar{s} \tag{2.62}$$

and therefore we can re-write equation (2.57) using equations (2.9) and (2.62) as

$$\beta_1 = \overline{B} + \lambda(\bar{b} - \bar{r}) \tag{2.63}$$

which suggests that an OLS regression of log earnings on schooling yields an upward-biased estimate of the average marginal return to schooling, with a bigger bias the larger the variance in ability relative to the variance in discount rates (i.e. the higher λ) . The term $\lambda(\bar{b} - \bar{r})$ is therefore an endogeneity bias that arises because people with higher marginal returns to education choose higher levels of schooling.

What implications does this model have for IV estimation procedures? If our instrumental variable is a discrete indicator representing an intervention that affects one subsample of individuals (the treatment group) but not the other subsample (the control group), then the IV estimate of the return to schooling has probability limit

$$p\lim \beta_1^{IV} = \frac{\overline{y_t} - \overline{y_c}}{\overline{s_t} - \overline{s_c}} \tag{2.64}$$

where $\overline{y_t}$ and $\overline{y_c}$ are the expectations of log earnings in the treatment and control group respectively, and $\overline{s_t}$ and $\overline{s_c}$ the corresponding expectations of schooling in the two groups. If all individuals have the same constant marginal return to education then $\overline{y_t} - \overline{y_c} = \overline{B}(\overline{s_t} - \overline{s_c})$ and the IV estimate is a consistent estimate of the average marginal rate of return to education in the population.

Card [51, pp19–20] goes on to consider the more general case where the control and treatment groups are divided into subgroups $g = 1, ...G$ with the property that individuals in each subgroup have (approximately) the same marginal return to schooling (B_g). He assumes there is some intervention that raises average education in subgroup g of the treatment population by $\Delta\overline{s_g}$ which implies the probability limit of the IV estimate of the return to education is given by

$$p\lim \beta_1^{IV} = \frac{\sum_{g=1}^{G} \Delta\overline{s_g} B_g w_g}{\sum_{g=1}^{G} \Delta\overline{s_g} w_g} \tag{2.65}$$

where w_g is the fraction of the population in subgroup g. This suggests that the instrumental variables estimator can exceed the conventional OLS estimator if the intervention affects a sub-population with a relatively high marginal return to schooling.

Card also shows that his model has implications for fixed effects estimators of the returns to education based on twins and sibling samples. He assumes that the marginal efficiency and marginal discount functions for sibling j from family i, can be decomposed as

$$b_{ij} = b_j + b'_{ij} \tag{2.66}$$

$$r_{ij} = r_j + r'_{ij} \tag{2.67}$$

where the sibling specific components are symmetrically distributed and orthogonal to the family components. Then the formula derived for the OLS regression coefficient in equation (2.60) remains valid, except now the variances and covariances of the ability and discount rate terms are interpreted as *within-family* variances and covariances[19]. In this formulation the comparison between the cross-sectional and within-family fixed effect estimator

[19]That is $\sigma_b^2 = var(b'_{i2} - b'_{i1})$, $\sigma_r^2 = var(r'_{i2} - r'_{i1})$, etc.

depends on the relative magnitude of λ in the overall population and within families. If variation in b_i is eliminated within families, then the within-family estimator should be below the cross-sectional estimator. On the other hand if the variation in r_i is eliminated within families and hence schooling choices are more highly correlated with ability within families than across the population, then the opposite will be true.

Card generalises his discussion to also allow for individual heterogeneity in the level of earnings (a_i) and measurement error. Incorporating these extensions, the probability limit of the OLS estimator is given by

$$p\lim \beta_1^{OLS} = \Psi \left[\overline{B} + \lambda \left(\overline{b} - \overline{r} \right) + k \left(\frac{\sigma_{ab} - \sigma_{ar}}{\sigma_b^2 + \sigma_r^2 - 2\sigma_{br}} \right) \right] \tag{2.68}$$

where σ_{ab} and σ_{ar} denote the covariances of (a_i, b_i) and (a_i, r_i) respectively. This implies that there are three sources of bias in the OLS estimator relative to the average marginal return to schooling $\overline{B}$. These are the attenuation bias due to measurement error (Ψ), the endogeneity bias which arises because people with higher marginal returns to education choose higher levels of schooling ($\lambda\overline{(b} - \overline{r})$) and heterogeneity bias due to unobserved components in the levels of earnings ($k(\sigma_{ab} - \sigma_{ar})/(\sigma_b^2 + \sigma_r^2 - 2\sigma_{br})$).

For the within-family estimator, the probability limit has the same form as that given in equation (2.68), with the attenuation ratio instead given by Ψ^*, and the re-interpretation of σ_b^2, σ_r^2, σ_{ab}, σ_{ar} and σ_{br} as within family variances and covariances. The IV estimator has the probability limit given in equation (2.65). If the intervention only effects one subgroup, then the IV estimator has probability limit $\overline{B_g}$ which is equal to the marginal return to education in the subgroup affected by the intervention. This could be above or below the average marginal return $\overline{B}$.

2.4.2 Estimating the Returns to Training

There is a large econometric literature dealing with the estimation of training effects with non-random selection. These include the papers of Ashenfelter

[9], Ashenfelter and Card [10], Bassi [16], and Heckman and Robb [101], [102] and [103]. In discussing the approaches to estimating the returns to training we look at earnings over two time periods and assume that individuals experience only one opportunity to participate in training in each time period, $t = 0, 1$. If they do participate in training between $t-1$ and t, then $D_{ti} = 1$. If they do not, then $D_{ti} = 0$. We can then write a general sequential model of the evolution of training and wages as

$$y_{0i} = X'_{0i}\beta_{00} + D_{0i}\alpha_{00} + A_i + \varepsilon_{0i} \tag{2.69}$$

$$\begin{aligned} y_{1i} &= X'_{0i}\beta_{01} + X'_{1i}\beta_{11} + D_{0i}\alpha_{01} + D_{1i}\alpha_{11} + A_i + \varepsilon_{1i} \\ &= x'_{1i}\beta_1 + d'_{1i}\alpha_1 + A_i + \varepsilon_{1i} \end{aligned} \tag{2.70}$$

where y_{ti} is the log of the real wage rate at time t of individual i; X_{0i} is a vector of exogenous individual characteristics (other than training) acquired by $t = 0$ and X_{1i} is a vector of individual characteristics at time $t = 1$ which affect wages (for example experience, race, gender and regional variables); A_i are unmeasured time invariant "permanent" correlated personal characteristics or unobserved ability (for convenience), ε_{ti} are transitory shocks to earnings at time t[20], $d'_{1i} = (D_{0i}, D_{1i})$ and $x'_{1i} = (X'_{0i}, X'_{1i})$. Participation in training in each period is determined by

$$D^*_{0i} = Z'_{0i}\zeta_{00} + v_{0i} = z'_{0i}\zeta_0 + v_{0i} \tag{2.71}$$

$$D^*_{1i} = Z'_{0i}\zeta_{01} + Z'_{1i}\zeta_{11} + v_{1i} = z'_{1i}\zeta_1 + v_{1i} \tag{2.72}$$

where $z'_{ti} = (x'_{t-1i}, c'_{t-1i})$[21]. In this formulation

$$D_{ti} = 1 \text{ if } \mathrm{D}^*_{ti} \geq 0 \text{ i.e. } \mathrm{v}_{ti} \geq -z'_{ti}\zeta_t,\ t = 0, 1 \tag{2.73}$$

[20]The error term could also contain an economy wide component e_t in each period (see Ashenfelter and Card [10]). In what follows we assume that this is uncorrelated with training (and our other explanatory variables) and forms part of the uncorrelated error term ε_{ti}.

[21]Because training can take place at any time between $t-1$ and t and our variables measuring individual characteristics are taken at time t, in this formulation we assume that training can only be determined by characteristics acquired by time $t-1$.

$$D_{ti} = 0 \text{ if } \mathrm{D}^*_{ti} < 0 \text{ i.e. } \mathrm{v}_{ti} < -z'_{ti}\zeta_t,\ t = 0, 1 \tag{2.74}$$

where the c_{t-1i} are observable individual characteristics which determine training participation, but not earnings, controlling for training.

If unobserved ability A_i, is correlated with training (or indeed any right hand side variable in the earnings equations), then OLS estimation of equations (2.69) and (2.70) will yield coefficient estimates which are biased. In addition, if the transitory earnings shocks ε_{ti} are correlated with training, then once again OLS estimation of equations (2.69) and (2.70) will yield coefficient estimates which are biased.

Controlling for Correlated Permanent Effects

There are generally two approaches used in the literature to control for correlated permanent effects. The first method involves eliminating the fixed effect by taking first differences, which gives

$$\begin{aligned} \Delta y_{1i} &= X'_{0i}(\beta_{01} - \beta_{00}) + X'_{1i}\beta_{11} + D_{0i}(\alpha_{01} - \alpha_{00}) \\ &\quad + D_{1i}\alpha_{11} + (\varepsilon_{1i} - \varepsilon_{0i}) \end{aligned} \tag{2.75}$$

This is the traditional fixed effects estimator and has been used in a number of training studies which are discussed below. If the observed individual characteristics X_{0i}, affect y_{1i} and y_{0i} in the same way (as we assume for the unobserved individual effects) then $\beta_{01} = \beta_{00}$ and the coefficients on X_{0i} in equation (2.75) will be zero. Similarly, if early training, D_{0i} affects wage outcomes identically then $\alpha_{01} = \alpha_{00}$. Clearly these are testable restrictions of the model.

The drawback of the first differenced specification lies in the MA error specification $(\varepsilon_{1i} - \varepsilon_{0i})$. The training measured by D_{0i} takes place before the shock in the period 1 wage is revealed and is possibly uncorrelated with ε_{1i}. However, recent training D_{1i} is quite possibly influenced by ε_{0i}. It is therefore difficult to argue that $(\varepsilon_{1i} - \varepsilon_{0i})$ is uncorrelated with D_{1i}. Past shocks to wages, at least, might be expected to induce participation in training. Also, this fixed effect approach, like the approach used in the twins and siblings studies, is open to measurement error problems.

The second method involves proxying the fixed effect and this was discussed earlier in the context of estimating the returns to schooling. Using this approach we assume we can proxy unobserved ability as

$$E(A_i|Q_i, x_{1i}, d_{1i}) = Q_i'\pi \tag{2.76}$$

and then run the extended regression

$$y_{1i} = x_{1i}'\beta_1 + d_{1i}'\alpha_1 + Q_i'\pi + \tilde{\varepsilon}_{1i} \tag{2.77}$$

where $\tilde{\varepsilon}_{1i} = A_i - E(A_i|Q_i, x_{1i}, d_{1i}) + \varepsilon_{1i}$ and $E(\tilde{e}_{1i}, D_{1i}) = 0$. As mentioned earlier, the ability to proxy the unobserved fixed (assumed to be unobserved ability here) effect is clearly going to depend on the quality of the data being used.

These estimators will only provide consistent estimates of the returns to training if selection into training is done on the basis of permanent unobserved individual effects. If, however, training, is correlated with current shocks to wages, ε_{1i}, we need to also take account of this to obtain unbiased estimates of the returns to training. This once again involves using instrumental variables techniques.

Controlling for Transitory Shocks

It is possible that transitory shocks to wages are also correlated with participation in training. This arises through the correlation of D_{1i} and ε_{1i} in equation (2.77) or alternatively D_{1i} with ε_{1i} and ε_{0i} in equation (2.75). For example, individuals with negative transitory wage disturbances, may decide to undertake training. To control for this type of bias, we need at least one instrument, c_{0i}', which is correlated with training, but uncorrelated with the transitory shocks in equations (2.75) and (2.77). Given these instruments we can perform the usual selectivity corrections of Heckman [97]. From equations (2.72) and (2.72) the selection adjustment term for the correlated transitory shock is given by

$$\widehat{\lambda}_{D_{1i}} = \frac{\phi(z'_{1i}\widehat{\zeta}_1)}{\Phi(z'_{1i}\widehat{\zeta}_1)} \text{ if } D_{1i} = 1 \tag{2.78}$$

$$\widehat{\lambda}_{D_{1i}} = \frac{-\phi(z'_{1i}\widehat{\zeta}_1)}{1 - \Phi(z'_{1i}\widehat{\zeta}_1)} \text{ if } D_{1i} = 0 \tag{2.79}$$

where $\widehat{\zeta}_1$ are the estimates obtained from a probit maximum likelihood procedure on training participation, and $\phi(.)$ and $\Phi(.)$ are the normal probability distribution and normal cumulative distribution functions respectively. Equations (2.75) and (2.77) can now be estimated by OLS with this selection term entering as an extra regressor. Again the standard errors in both equations have to be corrected to take account of the inclusion of a generated regressor.

Experimental Approaches

Another approach used in the literature, is to estimate training effects from field experiments where participants are randomly assigned to treatment (training) and control groups. A randomised experiment with an appropriately chosen control group is specifically designed to eliminate the correlation of any unobservable differences across individuals with the returns to training. LaLonde[112] for example, compared experimental estimates with traditional non-experimental econometric methods and found that many of the non-experimental methods did not replicate the experimentally determined results. However, an experimental estimation scheme cannot adjust for voluntary participation in training since (a) the participating group from which the controls are drawn is self-selected and (b) among those randomly selected for training some will, in fact, choose not to participate in training. As a result, what is estimated is the effect of training conditional on participation, and where participation is open to choice, self-selection bias may ensue. Moreover, although experiments of this type can assist evaluation, it is clearly not an optimal form of allocating training resources and it is difficult to envisage setting up a properly controlled experiment for non-government work related training schemes. Alternative experimental schemes can be devised that overcome some of these objections, but typically these reintroduce the kind of selection problems that we have just considered.

2.5 Critical Review of the Empirical Literature

2.5.1 Education and Earnings

What determines educational outcomes? What impact does education have on earnings outcomes? There have been numerous studies which have looked at the relationship between education and earnings and these studies have been comprehensively reviewed by Card [51], Willis [161] and Griliches [82]. In this section we review a small selection of this literature and distinguish the studies by the estimation techniques used.

Proxying Ability

Studies which have included an explicit proxy for ability include those by Griliches and Mason [86], Griliches [82], and Blackburn and Neumark [24].

The paper by Blackburn and Neumark specifically looks at whether the observed increase in the returns to schooling observed in the US of the 1980's was due to a changing relationship between schooling and ability. They use data from the US National Longitudinal Survey of Youth (NLSY) which has the results of scores of several tests measuring academic and technical ability as a proxy of inherent ability. They use data from the period 1979 to 1987 and initially estimate a wage equation like that shown in equation (2.33), where their exogenous explanatory variables consist of experience, age, a union dummy, a marriage dummy and an urban dummy as well as year dummies to control for cyclical factors. They also interact schooling with a time trend taking the value zero in 1979, to see whether the return to schooling has changed over the 9 year period[22]. Their OLS estimates suggest a return to education of around 3.2 per cent in 1979, increasing to almost 6 per cent by 1987.

They next include as an additional regressors, the sum of the individuals technical and computational test scores. This results in a reduction in the returns to education in all years with the return in 1979 now estimated to be around 1.2 per cent. The estimated rate of increase in the return over the nine year period is now, however, larger. They next assume that their measure of inherent ability is measured with error and follow the approach of Griliches and Mason [86] and use family background variables as instruments for the test score. This further reduces the estimates of the returns to schooling with the return in 1979 now insignificant, but the increase in the return to schooling is slightly larger again as a result of instrumenting the test score. This impact of ability on wage outcomes is now larger, as we would expect if ability was measured with error.

They then move on to deal with the endogeneity of schooling and use the same family background variables to instrument both the test score and schooling. When they only instrument schooling the level of the return to education in 1979 is just below the OLS estimate, but the increase well above. When they also instrument the test score, it is only the increase in schooling which is slightly dampened though the precision of these estimates are quite poor. They also interact ability and schooling and find that the increase in the schooling return has occurred only for workers with relatively high levels of academic ability.

[22]They also do this for age and union status.

Instrumental Variables Studies

Willis and Rosen [162] use data from the from the NBER-Th sample which is a sample of men who had volunteered for pilot, bombardier and navigator programs for the Army Air Force during World War II. The sample undertook a battery of tests of mental and physical ability and were resurveyed in 1955 and 1969. All of the individuals in the sample have at least high school education. Their approach is to assume that individuals choose levels of schooling which maximise the present value of lifetime earnings. Their education variable distinguishes high school graduates from individuals who continued with their education after completing high school. They also include some of the variables measuring ability and these are assumed to affect the individual's initial earnings and growth rate of earnings, given his schooling choice. Their instruments for education are a set of family background variables such as father's education and occupation, mother's work experience, religion and number of siblings. They find that individuals who continued on with education, have higher lifetime earnings from doing this than would have those who did not continue. Similarly those who did not continue with education, had higher lifetime earnings from not continuing than would have individuals who did continue. They therefore argue that the nature of selection bias is related to the fact that we do not observe non-optimal choices of individuals. This is the so called Willis and Rosen "comparative advantage" hypothesis.

Garen [75] uses a sample of men from the 1971 NLSY. Their instruments for schooling are a variety of family background variables such as parents education, father's occupation and number of siblings. They find that selection is important and that failure to correct for selection bias leads to underestimates of the returns to education. They argue that this is consistent with the comparative advantage hypothesis of Willis and Rosen [162] and the essence of selection bias is that we do not observe non-optimal choices. Individuals with unexpectedly large amounts of schooling, would have earned less than others if they had acquired less schooling, but with large amounts of schooling, they tend to earn more than others would have.

Butcher and Case [45] use data from the 1985 Panel Study of Income Dynamics (PSID), the National Longitudinal Survey of Women (NLSW) and Current Population Survey (CPS) and focus on white women aged 24 and over. Their instrument for the educational outcome of women is whether there are other sisters in the family. They find that women with one or more sisters undertake less education than women from similar sized families with only brothers. Their OLS estimate of the return to education from the PSID data is around 9.1 per cent. Their IV estimate is around 18.4 per cent, though it is imprecisely determined.

Card [50] uses a sample of NLSY men who were aged between 14 and 24 in 1966 and were working in 1976. His instrument for education is a dummy variable indicating a nearby college in the county in which the person was living in 1966. He finds that men who grew up near a 4 year college have significantly higher education than other men who did not. His OLS estimates of the returns to education are around 7.3 per cent and his IV estimate if around 13.2 per cent. He also tests whether this instrument can be legitimately left out of the wage equation by using nearby college interacted with parents education as instruments and then including nearby college as a dummy variable in the wage equation. He concludes that college proximity has no direct effect on wages. His IV estimate of the return to schooling using this procedure is 9.7 per cent.

Angrist and Krueger [5] use data from the 1970 and 1980 US Census and focus on men born between 1920–1929, 1930–1939 and 1940–1949. Their instrument for education is quarter of birth. They show that there is a quarterly pattern to completing school and they attribute this to the effects of schooling laws which govern the age at which a person can leave school. They find that men born early in the year have relatively low levels of schooling and earnings and argue that this arises because such people reach schooling leaving age at a lower grade than those who were born later in the year. Their OLS estimate of the return to schooling is 6.3 per cent and their IV estimate is 8.1 per cent.

Harmon and Walker [90] use data from the UK Family Expenditure Survey (FES) from 1978 to 1986 and use changes in the compulsory school leaving age as an instrument for educational outcomes. They find that men who faced a minimum school leaving age of 14, have significantly lower educational outcomes than those who faced a minimum school leaving age of 15 and 16. Their IV estimates of the return to schooling are in excess of 15 per cent compared with their OLS estimate of 6.3 per cent.

Miller and Volker [124] and [125] use data from the 1985 Australian Longitudinal Survey (ALS) and use family background variables as instruments for a persons highest education qualification. These variables identify such things as father's occupation, and mother's and father's education, type of school and family size. Their IV estimates of the returns to education are significantly lower for men (by around 12 per cent), but significantly higher for women (by around 10 per cent) than their corresponding OLS estimates.

Vella and Gregory [156] also use a sample of men from the ALS. They focus on men aged between 16 and 25 in 1985 who were employed in 1985 and in 1988. Their instrument for highest education qualification is a discriminatory index which measures the individual's views towards the equality of women in the workplace. They find that educational outcomes are higher for those individuals with a more egalitarian view of women's role in the workforce. They include family background variables in both the schooling and wage equations and while these are important in determining education outcomes, they are rarely significant in the wage equations. Their IV estimate of the returns to education are around 50 per cent higher than their OLS estimates. They argue, however, that there are important interactions between education and other determinants of wages. When they allow full interaction of their education variables with other explanatory variables in their wage equation, the resulting estimates of the returns to different levels of education lie between their OLS and non-interacted IV estimates.

Twin/Sibling Studies

Bradbury, McRae and Woyzbun [40] use sibling data from the 1985 and 1986 Australian Longitudinal Surveys (ALS) and find that within family returns to education were consistently lower than estimates which did not control for family based influences. They used a simple fixed effect model which exploits differences in the siblings' education and wage outcomes. Their estimates, however, are imprecisely determined and they do no take account of possible measurement error problems. They also find that while broadly similar results hold for brother and sister pairs, the returns among mixed pairs are much lower.

Blanchflower and Elias [25] use a sub-sample of twins from the British National Child Development Survey (NCDS) to estimate the returns to education for individuals aged 23 in 1981. Their results suggest upward bias in standard OLS estimates. They argue, however, that in comparison to non-twins in the NCDS sample, their twin sample is quite different and generalising results from twin studies to the rest of the population may be misleading.

Ashenfelter and Zimmerman [12] use sibling data from the National Longitudinal Survey (NLS) to estimate to what extent the correlation between schooling and earnings is due to the correlation between family background and schooling. They also examine the sensitivity of their results to the presence of measurement error. They conclude that OLS estimates of the return to schooling may be upward biased by around 25 per cent. They also conclude that after adjusting for measurement error[23], the intra-family estimate of the return to schooling is biased downward by around 25 per cent. They therefore conclude that the OLS estimate of the return to schooling suffers

[23]They assume that either 6.7 per cent or 20 per cent of the cross-sectional variance of schooling is attributable to measurement error.

from very little overall bias. Their sample, however, was quite small with only 143 brother pairs.

Ashenfelter and Krueger [11] use wage and schooling data for identical twins gathered at a US "twins festival" in August 1991. Their OLS estimate of the return to schooling is around 8.4 per cent[24]. They find that the fixed effects estimate of the returns to education is higher than the OLS estimate at around 9.2 per cent. The next use an IV within-family estimator where they instrument the difference in twins schooling outcomes with differences in the schooling levels of each twin pair *as reported by the other twin.* Conditional on the validity of their instrument, they conclude that measurement error imparts a considerable downward bias on the within-family estimator with the return to education now estimated to be around 16.7 per cent. They finally allow for the fact that there may be correlated measurement error within twin pairs and there estimate of the return to education allowing for this is around 13.2 per cent.

Other Fixed Effect Approaches

Angrist and Newey [7] use a sample of men from the NLSY who were aged 18 to 26 in 1983 and who were continuously employed between 1983 and 1987. In their sample, they observe some individuals acquiring more education over the period under examination and use fixed effects methods to estimate the returns to education. Their fixed effect estimate of the returns to schooling is 8.0 per cent compared to their OLS estimate of 3.6 per cent. They make no adjustments for possible measurement error in their fixed effects estimator.

Schmitt [143] uses data from the UK General Household Survey (GHS) to

[24] When they undertake GLS, rather than OLS estimation of the equations (1) and (2) they get an estimate of 8.7 per cent. When they include siblings education as an additional explanatory variable there GLS estimate of the return to education is 8.8 per cent with the coefficient on siblings education negative but not significant. Finally when they instrument own and siblings education with the twins report on the other's education they get a GLS estimate of the return to education of 11.6 per cent. The coefficient on siblings education is now more negative but still not significant at conventional levels.

focus on formal educational qualifications which have been obtained both in work and before commencing work. He separately identifies university qualifications, from 3 levels of vocational qualifications, teaching qualifications, nursing qualifications, A levels, more than 5 O levels, less than 5 O levels with clerical or commercial qualifications, other O level qualifications, clerical qualifications, apprenticeships, and other qualifications. Table 2.1 gives full details of the educational qualification variables that he uses.

Schmitt [143] finds that most type of educational qualifications have a significant impact on the log weekly earnings of males aged 16-64 between 1974 and 1988 with the biggest returns being obtained by men with University qualifications. His data does not have information on family background or ability variables which could be used as instruments for education and therefore his estimates of the *level* of the returns to skills may be biased. He therefore focuses on *changes* in the returns assuming that the effects of these biases are constant over time. He finds that the returns to high- and mid-level qualifications generally show a U-shaped pattern over the 15 year period, with the returns to these qualifications showing substantial gains over the 1980s which approximately offset declines during the late 1970s. The returns to the low-level qualifications (VOC3, OLEV, and APRNT) show almost no change over the 1970s. During the 1980's the differential for O Levels rises by approximately 5 per cent and the differentials for the two other vocational qualifications fall slightly.

What do the Empirical Studies Tell Us?

Clearly the results of these papers confirm that education results in higher wages being paid to individuals. They also provide quite a bit of evidence which suggests that schooling is endogenous and/or subject to measurement error. Most of the IV studies we looked at suggested that OLS underestimates the returns to education and contradict the conventional wisdom that

Table 2.1: Educational Qualification Variables used by Schmitt

Variable	Description
UNIV	UNIVERSITY: Higher Degree (Census Level A), First Degree, university diploma or certificate, qualifications obtained from colleges of further education or from professional institutions of degree standard (Census Level B).
VOC1	HIGHEST VOCATIONAL: Higher National Certificate (HNC) or Diploma (HND), BEC/TEC Higher Certificate or Higher Diploma, City and Guilds Full Technological Certificate, qualifications obtained from colleges of further education or from professional institutions below degree level but above GCE A Level standard.
TEACH	TEACHING: Non-graduate teaching qualifications (Census Level C).
NURSE	NURSING: Nursing qualifications (e.g. SEN, SRN, SCM).
ALEV	A LEVEL: GCE A Level, Scottish Leaving Certificate (SLC), Scottish Certificate of Education (SCE), Scottish University Preliminary Examination (SUPE) at Higher Grade, Certificate of Sixth Year Studies.
VOC2	MIDDLE VOCATIONAL: City and Guilds Advanced or Final, Ordinary National Certificate (ONC) or Diploma (OND), BEC/TEC National, General or Ordinary.
OLEV5+	MORE THAN 5 O LEVELS: Five or more subjects at GCE O Level obtained before 1975 or in grades A to C if obtained later, 5 or more subjects at SCE Ordinary obtained before 1973 or in bands A to C if obtained later, 5 or more subjects at CSE grade 1 or at School Certificate, SLC Lower, or SUPE Lower.
VOC3	LOWER-MIDDLE VOCATIONAL: City and Guilds Craft or Ordinary.
OLEVCC	LESS THAN 5 O LEVELS WITH CLERICAL OR COMMERCIAL QUALIFICATIONS: One to four subjects at GCE O Level or equivalent with clerical or commercial qualification such as typing, shorthand, book-keeping or commerce.
OLEV	LESS THAN 5 O LEVELS WITHOUT A CLERICAL OR COMMERCIAL QUALIFICATION.
CLER	CLERICAL OR COMMERCIAL QUALIFICATION WITHOUT O LEVELS.
APRNT	LOWEST VOCATIONAL: Miscellaneous apprenticeships.
OTHER	MISCELLANEOUS QUALIFICATIONS: Other qualifications including CSE Grades 2–5, plus all remaining qualifications which consist mainly of local or regional school leaving certificates and college or professional awards not regarded as 'higher education', i.e. not above GCE A level standard.
NOQUAL	NO QUALIFICATIONS: No qualifications including those with no formal schooling.

omitted ability bias results will upward bias OLS estimates. Part of this underestimation is undoubtedly due to measurement error in the schooling variables used in the studies, but it is far from clear that this is the whole story. In terms of Card's model, this can also occur if the interventions being relied on in IV estimation (for example changes in the school leaving age) affect individuals with high discount rates rather than low ability. In this case IV methods provide an estimate of the return to education for these marginal individuals which will be higher than OLS estimates which reflect average returns.

The within family studies are less conclusive with evidence suggesting that OLS may over or under estimate the returns to education. Measurement error is much more of a problem in these studies. However, the most recent evidence from Ashenfelter and Krueger [11] which explicitly deals with this measurement problem, again suggests that conventional estimates underestimate the returns to schooling. This can arise in Card's model if variation in discount rates are less within the family and schooling choices are more highly correlated with ability within the family, than in the population as a whole.

What the studies show is that it is crucial to understand what assumptions are being used by different econometric estimators of the returns to schooling and how these affect the resulting estimates. This ideally requires data which can exploit a number of these techniques and directly compare the results obtained using different procedures. The data used in this thesis will allow us to do this.

2.5.2 The Determinants and Returns to Work–related Training

A Selection of Empirical Training Studies

There have been a number of studies looking at the determinants of, and returns to, different types of training. A large majority of this literature focuses on the impact of Government Training schemes or formal educational qualifications. Studies which have specifically focused on more general work related training are less numerous. This Section presents a partial review of some of this literature, focusing on the studies of Greenhalgh and Stewart [80], Booth [33] and [34], Green [78], Lillard and Tan [115], Lynch [116], Blanchflower and Lynch [26] and Tan et. al. [153]. These studies have either looked at the determinants of non-government work related training and/or the effects of such training in terms of the wage outcomes received by individuals. Not all of the studies cited above correct for the possible endogeneity of training. Those which do use either fixed effect or IV estimation procedures. It should also be remembered that the studies cited above use data from a number of different surveys from different countries and none of the definitions of training used are directly comparable.

The study by Greenhalgh and Stewart [80] uses data from the British National Training Survey (NTS) of 1975. The NTS survey define "training" as anything which may have helped an individual to learn to do his or her work. Greenhalgh and Stewart [80] define this training as "vocational" if it helped an individual learn to do his or her work and was undertaken in relation to current or subsequent employment. "Non-vocational training" is defined as any adult and further education undertaken during the working lifetime.

Greenhalgh and Stewart [80] use this data to look at the determinants and effects of on- and off-the-job vocational training. The survey was conducted in 1975–1976 and has information on the retrospective work histories of more than 50,000 men and women in Great Britain. They found that women received substantially less full-time vocational training than men, and that neither men nor women received much part-time training. They find that the probability of receiving full-time training between 1965 and 1974 increased with the occupational status for men and single women and declined sharply with age. The probability of receiving full-time vocational training was less for non-white males though more likely for non-white married females, decreased with the number of children for both men and women, and was generally higher for people who had higher qualifications in 1965.

The also find that full-time vocational training yields significant returns, though the marginal benefit of training reaches zero once the individual has accumulated four weeks of vocational training. They also find that recent full-time vocational training results in larger returns for both single and married women than for men. Their dependent variable is not wages but occupational status, measured as the average male hourly earnings in the occupation in 1975. They deal with self-selection by exploiting the panel nature of their data using a first difference model (the change in occupational status between 1975 and 1965).

Booth [33] uses data from the 1987 British Social Attitudes Survey (BSAS). The data has information on whether an individual has been on any formal job-related training courses or received any formal job-related training in the preceding two years and the number of full days spent in such training. It also identifies whether individuals have received any informal training in the last two years, including practice to learn work; special talks/lectures; work with more experienced workers; visits to different parts of the organization; reading; teaching on-the-job; and teaching in courses.

She confirms Greenhalgh and Stewart's [80] finding that men have a much higher probability of receiving training than females. She also finds that training decreases with age, higher-level qualifications raise training probability, caring for children reduces training probability, larger establishments do more training and that public sector employees are much more likely to receive job-related training than their private sector counterparts.

She finds that training incidence has a large and significant impact on earnings especially for women. For men she finds that the incidence of training increases earnings by 11.2 per cent and for women by 18.1 per cent. It is not possible from the BSAS survey to derive an hourly wage and she instead has gross or total annual earnings as her dependant variable. Also, in her estimation procedure she treats training as exogenous and argues that this training effect may be over-estimated owing to self-selection.

Booth [34] uses data from the 1980 British National Survey of Graduates and Diplomats (BNSG). The BNSG data contains information about employer provided training received by the graduate from the time of their graduation in 1980 up until 1986-87 when the survey was undertaken. It has information on training received in up to four jobs. For each job the survey asks how many days were spent away from work on training courses during the first year of the job. It also asks for each job whether the employer organised for the respondent to have any formal training which is defined as training which was more than just learning as you do the job. For such training the survey distinguished between on-the-job formal training, courses within the company or organisation and courses outside the company or organisation.

In looking at the determinants of training she focuses on any training received in the persons's current job. She finds that the probability of men receiving this type of training decreases with age, is greater for non-whites, is higher for first class degree holders (though is less prevalent among people who have subsequently done postgraduate education) and increases with employer size. She finds that women receive less training in general than men and the determinants of training for women are quite different. In particular, for women the probability of training decreases with the number of children and first class degree holders receive less training than other types of graduates. For women there are, however, large positive increasing coefficients for employer size.

Booth [34] finds that training received in a person's current job has a significant return for both men and women graduates, especially training courses taken outside the company or organisation. Earnings also increase significantly with the number of days spent on training courses in the first year of the individuals current job. However training received in earlier jobs only offers a positive return for men. She interprets this as suggesting that training in earlier jobs is more portable for men than women. She deals with the endogeneity of training by using both a Heckman two-step procedure based on her earlier training probits and also uses a traditional fixed effect model. She finds no evidence of self-selection using the Heckman procedure, however her model does not appear to be properly identified[25]. In her fixed effects model, the dependent variable is the change in real log gross annual earnings between 1980 and 1986. The estimates of the training effects for men in this model are generally larger (though less precisely determined) than her corresponding OLS estimates. For women the OLS results remain largely in tact although the returns to outside training courses are now found to be negative (though not significant).

Green [78] uses data from the UK General Household Survey (GHS). The data he uses is from 1987 and distinguishes "training" from formal education and hence participation in certain types of further education are not counted as training including some day or block release education. "Training" in the GHS also includes "self-instruction", and a specific example given to interviewers of this is "teaching yourself to use a word processor over a period of time". Clearly, therefore the measures of training used by Green in his study are very different to those used by both Greenhalgh and Stewart [80] and Booth [34].

[25]All the explanatory variables appearing in her training probits, also appear in her wage equations.

He finds once again that the probability of training receipt is much larger for men than for women. For males, training (especially on-the-job training) declines significantly with age. For females training declines with age but less dramatically and for off-the-job training increases with age to a peak in the mid-30s. People with higher education are more likely to receive training and people with family responsibilities are less likely to receive training. People working in larger establishments, people in high status occupations and recent recruits are all more likely to receive job related training. Green, contrary to Booth [33], finds no evidence that public sector employees, *ceteris paribus,* receive more training than private sector workers.

Lillard and Tan [115] use data from three cohorts of the US National Longitudinal Survey of Youth (NLSY), the 1983 Current Population Survey (CPS) and the 1980 Employment Opportunities Pilot Projects Survey (EOPP). The training questions they use only refer to the longest training event in the interval since their last interview. The NLSY questions they use distinguish training by source (company, business/technical and other) and by type (managerial, professional/technical, semi-skilled and other). The data they use from the CPS allows them to distinguish between training which was used to get a person's current job and training designed to improve job skills and within these groups separately identify company, informal on-the-job and other training. The EOPP data distinguishes training by source (on-the-job, business/vocational schools and other).

They identify four main determinants of training. They find that a higher level of schooling attainment increases the likelihood of training, though the importance of schooling varies considerably across demographic groups, and for different types of training. For instance for young men in the NLSY, formal schooling is a complement for company training whereas the opposite is true of Business and Technical School Training. They also find that these schooling effects are less for women than men. They find that the likelihood of getting company and informal on-the-job training is greater in industries experiencing rapid technological change, especially for the most educated workers. Non-white males are significantly less likely to receive most types of private sector training however they find no such racial differences for women. They also find that training is less likely to occur in regions which have persistently high levels of unemployment relative to the nation as a whole.

They find that training has a positive impact on wages but the impact varies considerably by training source and type. From the NLSY data they find that company training has the greatest quantitative effect on increasing earnings and this effect persists for 13 years. The wage effects of training from other sources are much smaller and persist for only 8 to 10 years. When they look at the impact of training types on wage outcomes they find that managerial training has the most significant impact on earnings.

Tan et. al. [153] use data from the NLSY, the fourth wave of the NCDS (NCDS4) and the Australian Longitudinal Survey (ALS) to identify young male participation in company training and training from various outside sources. They use NLSY data to distinguish between company, business/technical, school or other training. The ALS is a panel survey of young Australians aged 16–25 in 1985 which commenced in 1985. The study uses data from the first four waves, that is up until 1988. In each year of the survey the respondents were asked about training received since the last interview. They use the survey to identify participation in company training, off-the-job training at technical and business colleges, and further schooling. The NCDS4 survey was conducted in 1981 when the cohort members were 23 years old. In this study Tan et. al. [153] use the monthly calendar data from the survey to create a longitudinal data set with one record for each 12 month period. The survey allowed them to identify up to four job related training events (lasting longer than 14 days) and four schooling courses. They use this information to distinguish company training, off-the-job training at colleges, industry centres and government skill centres as well as school courses for qualification.

They find that in general, the probability of getting most kinds of formal training rises with the level of schooling attainment though the evidence for Australia is quite weak. They find that the likelihood of company training is greater in high total factor productivity (TFP) industries in the US and Great Britain but not in Australia. They interpret these results as saying that in the US and Great Britain, employers operating in a growing and technologically progressive environment rely more on company training for skills needs and place less reliance on outside sources of training. They find that unions are associated with more formal training from most sources. They found marked differences across countries in the effects of work experience and tenure on training. Compared to British and Australian youth, they found that young men in the US received relatively little training when they first joined the workforce. However as their time on the job increased, the likelihood of receiving additional company training remained high, whereas in Australian and Britain it diminished.

They found that in all three countries company based training provided the largest returns followed by off-the-job training. The wage effects of outside training (excluding schools) were about one-half to two-thirds as large as those from company training. They found, however, that the size of the returns to training in the US were substantially larger than those in Britain and Australia. For instance they found that company training was associated with an initial increase in wages of around 18 per cent in the US compared with around 8 per cent in Australia and 7 per cent in Britain. Both Lillard and Tan [115] and Tan et. al. [153] treat training outcomes as exogenous, hence their estimates of the potential wage gains from training may be biased.

Lynch [117] also uses data from the NLSY. The NLSY questions on training depend on the specific year of the survey and the surveys used by Lynch [117] ask respondents whether in addition to schooling, military and government sponsored training programs, they received any other types of training *for more than one month.* Respondents were asked about training they had received over the survey year (up to three spells) and the dates of training periods by source. The sources of training identified were business college, nursing programs, apprenticeships, vocational and technical institutes, barber and beauty schools, correspondence courses and company training. She uses this information to identify three types of training: company training (on-the-job training), apprenticeships and training obtained outside the firm (off-the-job training). She also exploits the longitudinal nature of the data to distinguish between spells of training received whilst the person was with their current employer and that received in previous employment for each of the three types. She also distinguishes between completed and uncompleted spells of training received on the current job.

Because the NLSY only identifies spells of training which lasted at least four weeks (not necessarily full-time), Lynch's training variables are more likely to capture formal training spells rather than informal on-the-job training. She finds that females and non-whites are less likely to receive on-the-job training and apprenticeships although females are more likely to receive off-the-job training. Off-the-job training decreases with tenure, whilst on-the-job training increases with labour market experience. High school graduates are more likely to receive all three kinds of training and people with post high school education are more likely to receive both off and on-the-job training. Union members are more likely to receive on-the-job training and apprenticeship training . She confirms Lillard and Tan's finding that on-the-job training is less likely to occur in regions with relatively high unemployment rates but finds that the opposite is true for apprenticeship training. She also finds that individuals who have had on-the-job training with a previous employer are much more likely to receive on-the-job training in their current job.

Lynch [117] finds that receiving on-the-job, off-the-job and apprenticeship training results in higher wages for young people. She finds, however, that on-the-job training only has a significant impact on wages if it was provided by the person's current employer and concludes that on-the-job training is quite firm specific. She finds no evidence of self-selection into training, though her identification assumption is based on using eduction dummy variables in her training probits, and years of schooling in her wage equation. Her fixed effect estimates are broadly similar to her OLS estimates of the returns to training.

Blanchflower and Lynch [26] also use data from the NLSY and NCDS4. They use the NLSY data to identify whether individuals who were aged 25 in 1988 have had previous company training; previous off-the-job training; an apprenticeship; any company training with their current employer; off-the-job training during current employment; and whether they are still doing an apprenticeship. From the NCDS4 survey they identify whether individuals have trained with their current firm; have completed an apprenticeship with no qualifications, City and Guild Craft qualifications, or City and Guild Advanced qualifications; or whether they are still completing an apprenticeship at the time of the 1981 survey.

They find that in Britain, people who received training with their current employer (outside an apprenticeship) received on average about 2 per cent higher hourly earnings *ceteris paribus.* For both men and women, obtaining an apprenticeship also raised hourly earnings by around 2 per cent. For men, a City and Guild Craft Certificate conveyed an extra return of 2 per cent while a City and Guild Advanced Certificate conveyed a further 5 per cent return. They found no such positive certification effects for women. In the US in 1988, they find that spells of training provided by previous employers provide no return to current wages, whereas having some company training with an individual's current employer increased wages by 8 per cent (though this effect is only marginally significant). Males and females who had received off-the-job training in the past, received a wage premium of around 4 per cent. Having an apprenticeship raised earnings by 20 per cent for men, but had no effect for women. On the other hand, post high school education was found to have no effect of the wages of males, but large effects on those of women. In their study they treat training outcomes as exogenous.

Interpreting the Empirical Findings

From these studies a number of general hypotheses can be drawn as to the determinants of non-government work related training. The studies suggest that:

1. Males have better access to training than females.
2. Training decreases with age.
3. Higher education qualifications raise the probability of receiving training.
4. Industries with growing or changing technology provide more training.
5. Caring for children reduces training probability.
6. Union members receive more training than non-union members.
7. The probability of training decreases with job tenure.
8. Part-time workers receive less training than full-time workers.
9. Large establishments provide more training than small establishments.
10. Public sector establishments provide more training than private sector establishments.
11. Minority groups have a lower probability of receiving training.
12. Training probability is lower when unemployment is high.

It should be emphasised that the factors listed above are neither exhaustive nor universal. What is clear from the studies looking at this issue is that the determinants vary for different types of work related training and using highly aggregated descriptions of "training" miss important differences in the determinants of different forms training.

Different types of training would also appear to increase an individual's wage prospects. The magnitude and persistence of this training effect varies substantially across countries for different types of training and for different types of individuals.

In a large majority of the studies considered above, training is treated as exogenous. Some do use fixed effect estimation procedures to eliminate correlated fixed effects. Others use IV methods, but generally the identification relied on is very weak. No study of the returns to work related training controls for both correlated permanent *and* transitory effects. In this thesis, when we look at the determinants and effects of work related training in Britain in Chapter 6, we pay careful attention to the possible endogeneity of training and control for both correlated permanent and transitory effects. We find that controlling for this turns out to be very important in estimating the returns to different types of training in Britain.

2.6 Summary and Conclusions

Both the theoretical models and the empirical studies reviewed in this Chapter suggest that education and training confer significant wage advantages on individuals. The problem which arises in the empirical literature trying to estimate the true causal effect of education and training on wages relates to the fact that education and training are endogenous. This means that estimates which do not control for this endogeneity may over- or under- estimate the true economic returns to education and training.

There have been three main methods proposed in the economic literature for correcting for this endogeneity bias and the method chosen by researchers is often dictated by the data they have available. It is clear from the work reviewed in this Chapter, however, that different estimation procedures use different assumptions, and it is important to know the importance of these assumptions on the estimates obtained. This requires access to data which can exploit a number of these techniques so that direct comparisons can be made between different estimation techniques. The rich data used in this thesis allows us to do this.

Chapter 3

Birth Order, Family Characteristics and the Early Returns to Education in Australia

3.1 Introduction

In this Chapter we use data from the Australian Longitudinal Survey (ALS) and Australian Youth Survey (AYS) to estimate the returns to education for young people aged 16 to 25 between 1985 and 1991. There is a substantial literature currently in existence which shows that more highly educated individuals receive higher wages. However, as we saw in Chapter 2, estimating the actual magnitude of the returns to education can be biased if no account is taken of the fact that education is not randomly assigned across the population. A number of methods have been suggested in the literature to correct for these biases and there is currently much debate about which way these biases go. Most of the recent studies looking at this question have found that estimates which do not correct for these biases underestimate the returns to education whereas the earlier literature tended to find that the opposite was true.

The data we will use to look at these questions come from the Australian

Longitudinal Survey (ALS) and Australian Youth Survey (AYS) described in Chapter 1. In this Chapter we focus on the returns to education over the seven year period between 1985 and 1991. We concentrate on individuals aged 16 to 25 who have left full-time education and use instrumental variable techniques to deal with the endogeneity of education.

Studies using instrumental variable techniques need to identify at least one variable which affects education, but not wages controlling for education. This ideally requires identifying an exogenous source of variation in educational outcomes. Instruments which have been used in previous studies include changes in compulsory minimum school leaving age (Harmon and Walker [90]), season of birth (Angrist and Krueger [5]), proximity to educational institutions (Card [50]) and sibling composition (Butcher and Case [45]). These studies were reviewed in Chapter 2. None of these potential instruments are available in our sample[1].

We instead argue that an individual's birth order (measured by the number of older siblings), controlling for family size, is a crucial factor in determining educational outcomes. We find that educational outcomes deteriorate significantly, the more older siblings an individual has, controlling for family size and year of birth[2]. Clearly the number of older siblings an individual has is exogenous, given family size. This suggests that the number of older siblings is also a potential instrument for education in a wage equation controlling for family size if it can be legitimately left out of the wage equation. In addition we follow the approach of studies like Garen [75], Blackburn and

[1]For the AYS data we do know month of birth, but this is not available for individuals from the ALS sample. We have no information on proximity to educational institutions and over this period there has been no changes to the compulsory school leaving age. We also do not generally know the gender of siblings unless they live in the household with the individual.

[2]Clearly, because we have such a young sample, there are a number of young people in our sample who are less likely to have completed their desired level of education, even though they have left full-time education. For this reason in our schooling reduced form equations we also include year of birth dummies so that we do not conflate things like birth order effects with cohort effects.

Neumark [24], and Miller and Volker [124] and also use a range of family background variables such as mother's and father's education and occupation, and variables identifying the type of school the person attended as instruments.

Our instrumental variables estimates suggest that OLS estimates of the returns to education significantly *underestimate* the returns to education and qualifications for women, and the returns to qualifications for men. Our IV estimates of the returns to education are around 10 per cent higher than our OLS estimates for women and this difference is statistically significant. The IV estimates of the returns to different qualifications for both men and women are between 10 to 20 per cent higher than our corresponding OLS estimates.

In our sample there are also significant gender wage differentials despite the fact that our cohort is still relatively young. These gender differentials are largest for middle skilled individuals. There are, however, no significant gender wage differentials for individuals with less than 10 years of schooling as well as for those with a degree. With the exception of the lowest qualification group, the observed raw differences in the wages of women and men decrease with each education level. . The gender differentials that we do observe at each education level and for the sample as a whole partly reflect differences in the average characteristics of men and women, and partly differences in the prices paid to observed characteristics. The importance of these two effects varies by education groups.

In section 2 we review some of the studies which have considered birth order effects. In section 3 we look more closely at the ALS and AYS data used in this analysis. In section 4 we outline our estimation methodology. The results of our work are given in section 5 and the major findings of our analysis are summarised in section 6.

3.2 Birth Order, Family Characteristics and Educational Attainment

As we saw in the previous Chapter economic models proposed by such people as Becker [19] suggest that under certain circumstances, a child's education can depend on factors such as their gender, the size of their family, parental interest in the child's education, the child's birth order, and/or the sex composition of their sibship. In this Chapter, we focus on the role of birth order.

Research in other disciplines suggests that there are competing theories as to whether earlier or later born children should have better education outcomes. It is clear from the literature that the exact role that factors like birth order play in determining educational outcomes remains an empirical question. There have been a number of empirical studies looking at birth order effects including those of Behrman and Taubman [22], Kessler [108] and Hauser and Sewell [93].

Behrman and Taubman [22] uses data which consists of the offspring of twins in the National Academy of Science/National Research Council twin survey. The paper specifically looks at birth order, schooling and earnings. They find significant birth order effects on schooling, with earlier born individuals doing better than later born individuals. They find no birth order effect on earnings, once family size is controlled for. The sample they use are relatively young, ranging between 20 to 35 years. Because of the way the data has been collected, the later born children are also younger and it is difficult to separate age and cohort effects from birth order effects. They attempt to do this by putting in age and age squared variables in their schooling equation but Griliches [84] questions the validity of this procedure given the fact that in such a young sample, younger individuals (which by construction are the later born individuals) will not have finished their desired schooling. It is clear that in order to assess the importance of birth order effects, we need to be able to separate out cohort effects. This requires a sample where the distribution of birth order does not depend on the age of the sample.

The study by Hauser and Sewell [93] uses a sample of 9000 Wisconsin high school graduates of 1957 and their full sibship which consists of over 30000 individuals. They find that there are no significant or systematic effects of birth order on schooling when other relevant variables are controlled for, particularly family size and the general increases in schooling that have occurred across families over time.

Finally the study by Kessler [108] uses data from the NLSY to look at the effects of birth order on wage determination and employment status over time. He finds that neither birth order, or family size significantly influence the level or growth rates of wages.

From these studies there is some evidence that birth order may affect educational outcomes, even controlling for family size. The studies suggest, however, that birth order has no affect on wage outcomes, after controlling for family size. The number of older siblings an individual has is exogenous, given family size. This suggests that the number of older siblings (or some other measure of birth order) is a potential instrument for education in a wage equation controlling for family size if it can explain educational outcomes and can be legitimately left out of a wage equation, controlling for education. We look at this issue in more detail below.

3.3 The Data

The ALS and AYS have data on the labour market activity and wages of 16 to 25 year olds for the period 1985 to 1991. We do not have complete coverage for all ages over the 7 year period. For 16 year olds we do not have data for 1986, 1987 and 1988; for 17 year olds we do not have data for 1987 and 1988; and for 18 year olds we do not have data for 1988. This arises because the ALS, unlike the AYS, did not introduce a new cohort of 16 year olds after 1985. The age distribution of our sample over the seven year period is given in Table 3.8 in Appendix A.3.1.

3.3.1 Education Variables

In Australia school is compulsory until the age of 15 and this effectively means that most, though not all, students complete at least 10 out of a possible 12 years of schooling. In order to go onto further study at a University, students must complete Year 12 (the final year of school). An undergraduate university degree generally involves 3 years of full-time study. There are also other forms of tertiary education which do not necessarily require completion of Year12. These qualifications (generally diplomas or certificates) are provided by Technical and Further Education (TAFE) colleges or other business schools or colleges. These qualifications include apprenticeship and trade qualifications and generally take the equivalent of two years full-time study, though a large proportion of individuals completing these courses do so on a part-time basis. In order for individuals to undertake post-graduate qualifications they generally require undergraduate degrees at an "honours" level which adds one year to an ordinary undergraduate degree. Post-graduate Masters degrees generally involve a further one years full-time study whereas PhDs generally involve a minimum of three years full-time study.

Our data does not have a measure of the number of years of education. We do, however, know the individuals highest school qualification, the first qualification they obtained after leaving school as well as their most recent highest qualification. We use this information to construct a measure of the individual's years of education based on the normal time it takes to complete the qualification(s) full-time. By construction, this variable ranges between 8 years and 17 years[3] and is at best a crude proxy of educational attainment. In the analysis that follows below, we estimate the returns to education

[3]In constructing this measure of education we assume that individuals with two university degrees have undertaken 5 years of education since leaving school. Individuals undertaking PhDs are unlikely to have entered the labour market by the age of 25 so this seems like a reasonable assumption.

treating this measure of years of education as both a continuously observed and a latent variable.

Our years of education variables is constructed solely from information on qualifications the individual has undertaken. A more sensible use of this information is th use this information directly. The measures of educational attainment which have generally been used in the Australian context involve identifying an individual's highest educational qualification. A year of education undertaken in a University, is very different to a year of education undertaken at a vocational institution and this heterogeneity in education is not accounted for if the measure of educational attainment is in terms of years of full-time study. The ALS and AYS data have direct measures of the individual's highest educational qualifications and we use this information to identify the persons highest school and post-school qualification. These qualifications, like years of education, have a definite ordering. Our base group is individuals who completed less than 10 years of schooling. We then identify those who completed Year 11 , those who completed Year 12 but undertook no post-school qualifications, those who completed Year 12 and undertook a diploma or certificate, and finally those who completed Year 12 and also completed a university degree. We also separately identify those individuals who did not complete all 12 years of school, but who have subsequently obtained a diploma or certificate.

We also have information on the type of school the individual attended (Government, Roman Catholic, or Private) and in which State they last attended school. School education policy in Australia is controlled by individual State and Territory Governments and not by the Federal Government. As a result, school curriculum, school starting and finishing ages and assessment procedures vary widely by State.

3.3.2 Individual and Family Background Variables

The AYS and ALS data has extensive measures of an individuals family background. We use the data to construct variables identifying the mother and father's occupation when the individual was 14, whether the individual's parents have a degree or some other tertiary qualification, the race of Australian born individuals[4], whether his/her parents were born in Australia, whether the individual lived in a capital city (the base group), some other city, a country town, a rural area or overseas at age 14, whether the individual lived with both parents (the base group), their mother only, their father only or neither parent at age 14, whether English was their first language (base group) and for individuals for whom English was a second language (ESL) we distinguish individuals with good English skills from those whose skills were poor at the age of 14. We also construct variables measuring the number of siblings the individual has, and the number of older siblings.

We also construct year of birth dummy variables, age variables and regional dummy variables identifying the individual's State of residence[5].

3.3.3 Labour Market Variables

We exclude from our sample any individuals who are still undertaking full-time education or are not employed. This selection may of course bias our estimates. For those individuals who have completed full-time education and are employed (either full-time or part-time), we construct a measure of their real hourly wage (in 1984/85 dollars). We also construct a measure of their potential labour market experience defined as their age minus years of schooling minus five.

[4]Race questions are only asked for individuals born in Australia. Thus our base group is all individuals born overseas.

[5]The regional variables identify the State of residence. The 1986, 1987 and 1988 ALS surveys do not identify the state in which the individual lives. For these years we assume that they have remained in the State of their residence at the time of the 1985 survey.

3.3.4 The Final Sample

This leaves us with a final sample of 12703 males and 10859 females who were born between 1960 and 1975. Summary statistics for the sample are given in Table 3.9 in Appendix A.3.2.

3.4 Methodology

3.4.1 Estimating the Returns to Education

There are a number of approaches to estimating the returns to education as we saw in Chapter 2. Following the approach outlined in that chapter we begin by using a two equation system

$$w_i = s_i\beta_1 + X_i'\beta_2 + u_i \tag{3.1}$$

$$s_i = Z_i'\gamma + v_i \tag{3.2}$$

where s_i is years of schooling (full-time years of education), w_i is the log of the real hourly wage rate, X_i and Z_i are vectors of exogenous observed individual characteristics, β_1 is the return to education, and u_i and v_i are a pair of residuals. OLS estimation of equation (3.1) gives rise to an unbiased estimate of the return to education if u_i and v_i are uncorrelated, that is if s_i is exogenous in the wage equation ($E(s_i u_i) = 0$).

Instrumental variable approaches identify a set of exogenous variables that affect the education decision, but not earnings controlling for education. In order for the model to be identified we need variables in our Z_i can be legitimately be left out of the earnings equation (3.1) while being significant determinants of our education variable in equation (3.2). Thus we have $Z_i' = (X_i', W_i')$ where W_i is a vector containing at least one variable for identification. In our study we use family background variables, family composition variables and variables identifying the type of school the individual last attended. Our schooling equations also include year of birth dummies to capture cohort effects. Our exogenous explanatory variable in the wage equation (X_i), consist of gender, race variables for Australian born individuals, dummy variables identifying English proficiency for individuals for whom English was a second language (ESL) as well as regional and year dummy variables[6]. Experience variables are also included in our wage equation, but we treat these as endogenous[7]. We also include the a variable controlling for the number of siblings the individual has. We initially carry out IV estimation treating our years of education variable as a continuous variable. This is equivalent to estimating the following wage equation

$$w_i = s_i\beta_1 + X_i'\beta_2 + \alpha\widehat{v}_i + \eta_i \tag{3.3}$$

where $\widehat{v}_i$ are the residuals from OLS estimation of equation (3.2), and $E(s_i\eta_i) = 0$ by construction. A Hausman t test of the exogeneity of schooling is given by testing $\alpha = 0$ in equation (3.3)[8].

Previous studies looking at the returns to education in Australia suggest that education is not a continuous variable[9]. We have two measures of educational outcomes both of which are ordered. Hence for both of these different measures we also use a latent variable model of the form

$$s_i^* = Z_i'\gamma + v_i \tag{3.4}$$

where

$$s_{ij} = 1 \text{ if } \mu_{j-1} < s_i^* \leq \mu_j \tag{3.5}$$

where $j = 0, 1, 2, 3...$ and $\mu_{j-1} < \mu_j$. The education equation is now estimated as an ordered probit and the parameter estimates are used to calculate the

[6]In earlier versions of this work, we also interacted schooling with a time trend to see how the returns to education had changed over time, controlling for year effects. There was no evidence of changes in the returns to education for women, and only marginal evidence of a decline for men over the period 1985 to 1991.

[7]Experience in our data has been defined as age minus years of education minus five. Since years of schooling is endogenous in our set up, years of experience is also endogenous.

[8]See Smith and Blundell [148].

[9]See Miller and Volker [124] and [125] and Vella and Gregory [156] for example.

usual Heckman [97] selection adjustment term

$$\widehat{\lambda}_i = \frac{\phi(\widehat{\mu}_j - Z_i'\widehat{\gamma}) - \phi(\widehat{\mu}_{j+1} - Z_i'\widehat{\gamma})}{\Phi(\widehat{\mu}_{j+1} - Z_i'\widehat{\gamma}) - \Phi(\widehat{\mu}_j - Z_i'\widehat{\gamma})} \tag{3.6}$$

where the $\widehat{\mu}_j$'s and $\widehat{\gamma}$ are the estimates obtained from the ordered probit maximum likelihood procedure, and $\phi(.)$ and $\Phi(.)$ are the normal probability distribution and normal cumulative distribution functions respectively. We can then estimate the following wage equation

$$w_i = s_i'\beta_1 + X_i'\beta_2 + \varphi\widehat{\lambda}_i + \eta_i \tag{3.7}$$

where s_i is now either years of education or a vector of dummy variables identifying the person's highest qualification. This specification my be less robust than equation (3.3) because we require an additional assumption of normality. In estimating both equations (3.3) and (3.7) our standard errors are corrected to take account of the generated regressor in the equations as well as heteroscedasticity[10].

3.4.2 Education and Gender Wage Differentials

The mean difference in the observed wages of men and women in terms of log differences, or gender gap ($\widehat{g}$) is given by

$$\widehat{g} = \overline{x}_m'\widehat{\beta}_m - \overline{x}_f'\widehat{\beta}_f \tag{3.8}$$

where $\overline{x}_m$ and $\overline{x}_f$ are vectors containing the means of all the explanatory variables in our male and female wage equations (except selection terms which have a mean of zero for the whole sample) and $\widehat{\beta}_m$ and $\widehat{\beta}_f$ are the corresponding estimated coefficient vectors. Following the approach of Stewart [154][11] and Juhn, Murphy and Pierce [107] we can rewrite this expression as

$$\widehat{g} = (\overline{x}_m - \overline{x}_f)'\widehat{\beta}_m + \overline{x}_f'(\widehat{\beta}_m - \widehat{\beta}_f) = \widehat{g}_c + \widehat{g}_p \tag{3.9}$$

[10]See Arellano and Meghir [4] for details.

[11]Stewart uses this type of decomposition when looking at union wage markups.

which decomposes the observed gender wage differentials into two effects[12]. The first is the difference in observed wages which arises because men and women have different observed characteristics, for instance education and labour market experience. The second is the differences in observed wages which is a result of men and women being "paid" differently for a given set of characteristics. This is the estimated differential which exists once background has been controlled for or *ceteris paribus* gender wage differential. If observed gender wage differentials primarily reflect differences in observed characteristics then the policy response will be different than if they primarily reflect differences in the "price" paid for the observed characteristics of women. The mean gender wage gap of any subgroup s, of our sample, for instance individuals with a particular educational qualification, can be calculated by replacing the mean characteristics of males and females with those of the subgroup s of interest, $\overline{x}'_{sm}$ and $\overline{x}'_{sf}$ in equation (3.9).

3.5 Results

3.5.1 Determinants of Education Outcomes

From our data we have constructed two measures of educational outcomes. The first is years of full-time education and the second involved identifying the highest qualification a person has received. Both of these education variables are ordered. In Tables 3.1 and 3.2 we present the results of our various schooling equations for males and females respectively. Results for the whole sample are given in Table 3.10 in Appendix A.3.3. It should be emphasised that these equations are not structural models of the determinants of educational outcomes. They are merely reduced form equations which form the first stage of our IV estimation procedure. In the first column of these tables we present the results from our reduced form years of education regression

[12] An alternative way of doing this decomposition is as $\widehat{g} = (\overline{x}'_m - \overline{x}'_f)'\widehat{\beta}_f + \overline{x}'_m(\widehat{\beta}_m - \widehat{\beta}_f)$. It is, of course, an arbitrary decision which one we choose.

where we have treated years of education as continuous. In the next column we present the results of our alternative model where years of education are treated as latent and instead estimated by ordered probit. In the final column we present the results of our highest qualification ordered probit equation.

All three equations in Table 3.1 give very similar results as to the determinants of educational outcomes for men. The first point to emerge is that men of more highly educated parents (those with degrees or other tertiary education) have better education outcomes than men from less educated parents (those with only schooling qualifications). It is also true that sons whose fathers work in more highly skilled occupations do significantly better than sons whose fathers work in relatively unskilled jobs or are unemployed (the base group). Mother's occupational status when the child was fourteen does not, however, appear to be important for men's educational outcomes. Men who lived with their mother or father only at 14, or with neither parent, also have lower educational attainment than individuals who lived with both parents (the base group). Country of parent's birth also seems important, with men from Australian born fathers (in the years of education specification) and overseas born mothers doing significantly better.

The region where the child lived at 14 is also important. Men who lived in country towns or rural areas at this age do significantly worse than men who lived in a capital city (the base group), a non-capital city or overseas at that age. White Australian born males tend to have better educational outcomes than non-white males or overseas born males (the base group), but interestingly, men who have English as a second language (ESL) but who had good English language skills by the age of 14 do better than those with ESL and poor English skills and those whose first language was English (the base group).

The State in which the man last went to school and the type of school he went to, are also important in determining educational outcomes. Men from all States except Tasmania and Western Australia have significantly

Table 3.1: The Determinants of Male Education Outcomes

Variable	Years of Full-time Education				Highest Qualification	
	Coef.	(S.E.)	Coef.	(S.E.)	Coef.	(S.E.)
Constant	12.007	(0.138)				
Australian Born White	0.250	(0.054)	0.167	(0.038)	0.125	(0.038)
Australian Born Non-white	-0.114	(0.106)	-0.112	(0.075)	-0.048	(0.076)
Mother Born Australia	-0.275	(0.046)	-0.187	(0.032)	-0.142	(0.032)
Father Born Australia	0.103	(0.043)	0.072	(0.030)	-0.022	(0.031)
English Good (ESL)	0.342	(0.064)	0.221	(0.045)	0.327	(0.045)
English Poor (ESL)	0.021	(0.169)	0.040	(0.118)	0.046	(0.120)
Other City at 14	-0.002	(0.039)	-0.002	(0.027)	-0.049	(0.027)
Country Town at 14	-0.135	(0.035)	-0.098	(0.025)	-0.158	(0.025)
Rural Area at 14	-0.113	(0.048)	-0.082	(0.034)	-0.204	(0.034)
Overseas at 14	0.072	(0.132)	0.067	(0.093)	-0.010	(0.094)
Lived with mother only at 14	-0.192	(0.076)	-0.161	(0.053)	-0.114	(0.055)
Lived with father only at 14	-0.065	(0.093)	-0.070	(0.065)	-0.159	(0.067)
Lived with neither parent at 14	-0.445	(0.142)	-0.405	(0.100)	-0.394	(0.102)
Mother Degree	0.380	(0.069)	0.258	(0.048)	0.232	(0.049)
Mother Other Tertiary	0.204	(0.041)	0.155	(0.029)	0.122	(0.030)
Father Degree	0.410	(0.055)	0.259	(0.039)	0.411	(0.039)
Father Other Tertiary	0.202	(0.050)	0.138	(0.035)	0.089	(0.036)
Father Manager/Professional	0.258	(0.068)	0.187	(0.048)	0.209	(0.049)
Father Salesperson/Clerk	0.100	(0.077)	0.078	(0.054)	0.185	(0.055)
Father Tradesperson	-0.005	(0.070)	-0.005	(0.049)	-0.003	(0.050)
Father Manual	-0.204	(0.070)	-0.155	(0.049)	-0.158	(0.050)
Mother Manager/Professional	0.010	(0.042)	0.014	(0.030)	0.092	(0.030)
Mother Salesperson/Clerk	0.006	(0.036)	0.007	(0.025)	-0.011	(0.026)
Mother Tradesperson	-0.074	(0.103)	-0.043	(0.072)	-0.099	(0.074)
Mother Manual	-0.075	(0.046)	-0.047	(0.032)	-0.031	(0.033)
Number of siblings	-0.076	(0.011)	-0.056	(0.008)	-0.054	(0.008)
Number of older siblings	-0.031	(0.012)	-0.023	(0.009)	-0.019	(0.009)
School Victoria	0.008	(0.035)	0.011	(0.024)	0.171	(0.025)
School Queensland	0.223	(0.041)	0.168	(0.029)	0.288	(0.029)
School South Australia	0.440	(0.050)	0.316	(0.035)	0.376	(0.036)
School Western Australia	-0.052	(0.052)	-0.025	(0.036)	-0.025	(0.037)
School Tasmania	-0.456	(0.075)	-0.324	(0.053)	-0.266	(0.054)
School Northern Territory	0.336	(0.143)	0.256	(0.100)	0.173	(0.100)
School ACT	0.695	(0.127)	0.488	(0.089)	0.723	(0.091)
Catholic School	0.360	(0.038)	0.257	(0.027)	0.285	(0.027)
Private School	0.656	(0.059)	0.459	(0.042)	0.636	(0.042)
μ_1			-2.804	(0.104)	-1.752	(0.100)
μ_2			-2.057	(0.099)	-0.267	(0.099)
μ_3			-0.855	(0.097)	0.366	(0.099)
μ_4			-0.331	(0.097)	1.243	(0.100)
μ_5			0.701	(0.097)	1.772	(0.100)
μ_6			0.968	(0.097)		
μ_7			1.427	(0.098)		
μ_8			2.347	(0.101)		
μ_9			2.696	(0.106)		
Number of observations	12703		12703		12703	
P-value Year Born Dummies	0.000		0.000		0.000	
Log Likelihood	-22934.16		-21330.25		-18739.33	
(Pseudo) R^2	0.1805		0.0545		0.0544	

better educational outcomes than men who went to school in New South Wales (the base group). This presumably reflects the different school educational systems operating in the States with the schooling curriculum in New South Wales being very much geared towards University entrance rather than broader vocational training. Men who attended Catholic schools or other Private Schools have significantly better educational outcomes than men who attended Government schools.

It is also clear from the Table that family composition and order of birth are both very important determinants of educational outcomes, even after controlling for other socio-economic status variables. Educational outcomes are significantly worse for individuals who come from large families. Moreover, given family size, individuals with more older siblings do significantly worse than those with less older siblings. The negative effect of family size has been found in many studies of the determinants of education and presumably reflects such things as family wealth and resources. The older sibling effect, however, suggests that within families, family composition has an important impact on men's educational attainment. In the sample used in this Chapter, the position in the family is not related to the age of the individual which is different from the data used by Behrman and Taubman [22]. We also have included year of birth dummies to control for cohort effects rather than age. As mentioned in the introduction, birth order given family size is exogenous and is therefore a potential instrument in a wage equation controlling for family size and education.

The results for women reported in Table 3.2 are broadly consistent with those reported for men. Parental education variables are once again important determinants of women's educational outcomes. For women, mother's occupation at 14 is a much more important determinant of educational outcomes than for men. For women family size (measured by number of siblings) is no longer generally significant, but number of older siblings is once again negative and significant. In Table 3.10 of Appendix A.3.3 we report the re-

Table 3.2: The Determinants of Female Education Outcomes

Variable	Years of Full-time Education				Highest Qualification	
	Coef.	(S.E.)	Coef.	(S.E.)	Coef.	(S.E.)
Constant	12.347	(0.151)				
Australian Born White	0.214	(0.059)	0.147	(0.041)	0.102	(0.042)
Australian Born Non-white	-0.074	(0.113)	-0.035	(0.079)	-0.063	(0.080)
Mother Born Australia	-0.225	(0.048)	-0.162	(0.033)	-0.139	(0.034)
Father Born Australia	-0.043	(0.044)	-0.009	(0.031)	-0.012	(0.031)
English Good (ESL)	0.216	(0.069)	0.187	(0.048)	0.218	(0.049)
English Poor (ESL)	-0.388	(0.241)	-0.275	(0.169)	-0.128	(0.170)
Other City at 14	-0.121	(0.042)	-0.092	(0.029)	-0.089	(0.030)
Country Town at 14	-0.098	(0.038)	-0.072	(0.027)	-0.076	(0.027)
Rural Area at 14	-0.024	(0.054)	-0.030	(0.038)	-0.063	(0.038)
Overseas at 14	-0.167	(0.140)	-0.120	(0.097)	-0.299	(0.098)
Lived with mother only at 14	0.003	(0.084)	-0.043	(0.059)	-0.158	(0.059)
Lived with father only at 14	0.023	(0.098)	-0.007	(0.068)	0.072	(0.069)
Lived with neither parent at 14	0.096	(0.142)	0.026	(0.099)	-0.025	(0.100)
Mother Degree	0.538	(0.070)	0.374	(0.049)	0.421	(0.050)
Mother Other Tertiary	0.302	(0.047)	0.229	(0.033)	0.259	(0.033)
Father Degree	0.536	(0.057)	0.341	(0.040)	0.379	(0.041)
Father Other Tertiary	0.547	(0.059)	0.369	(0.041)	0.341	(0.042)
Father Manager/Professional	0.285	(0.076)	0.175	(0.053)	0.145	(0.053)
Father Salesperson/Clerk	0.327	(0.086)	0.219	(0.060)	0.143	(0.061)
Father Tradesperson	0.156	(0.079)	0.097	(0.055)	0.016	(0.056)
Father Manual	-0.027	(0.079)	-0.049	(0.055)	-0.132	(0.056)
Mother Manager/Professional	0.260	(0.047)	0.189	(0.033)	0.201	(0.033)
Mother Salesperson/Clerk	0.089	(0.038)	0.075	(0.027)	0.116	(0.027)
Mother Tradesperson	0.033	(0.104)	0.010	(0.072)	0.085	(0.073)
Mother Manual	-0.074	(0.049)	-0.060	(0.034)	-0.037	(0.034)
Number of siblings	-0.014	(0.013)	-0.014	(0.009)	-0.005	(0.009)
Number of older siblings	-0.076	(0.013)	-0.054	(0.009)	-0.059	(0.009)
School Victoria	0.191	(0.038)	0.157	(0.027)	0.324	(0.027)
School Queensland	0.349	(0.044)	0.256	(0.031)	0.346	(0.031)
School South Australia	0.367	(0.053)	0.299	(0.037)	0.474	(0.037)
School Western Australia	0.062	(0.057)	0.069	(0.040)	0.132	(0.041)
School Tasmania	-0.428	(0.078)	-0.334	(0.055)	-0.243	(0.056)
School Northern Territory	0.116	(0.152)	0.132	(0.106)	0.297	(0.106)
School ACT	0.272	(0.153)	0.245	(0.107)	0.558	(0.108)
Catholic School	0.369	(0.040)	0.271	(0.028)	0.219	(0.028)
Private School	0.968	(0.062)	0.630	(0.044)	0.632	(0.045)
μ_1			-3.160	(0.119)	-1.963	(0.109)
μ_2			-2.336	(0.108)	-0.502	(0.107)
μ_3			-1.144	(0.106)	0.119	(0.107)
μ_4			-0.530	(0.106)	0.948	(0.108)
μ_5			0.494	(0.106)	1.727	(0.108)
μ_6			0.744	(0.106)		
μ_7			1.276	(0.106)		
μ_8			2.099	(0.109)		
μ_9			2.403	(0.111)		
Number of observations	10859		10859		10859	
P-value Year Born Dummies	0.000		0.000		0.000	
Log Likelihood	-19633.49		-18330.57		-16463.58	
(Pseudo) R^2	0.1802		0.0542		0.0598	

sults for the male and female sample as a whole. The results from this table suggest that the educational outcomes of women are significantly higher than those of men in our sample.

3.5.2 Estimates of the Returns to Education

The Returns to Years of Education

Table 3.3 reports the results for men of our OLS and IV estimation procedures. In the first column we report the OLS estimates of the returns to education. The second column reports the results of the conventional IV approach and the final column reports the results from our alternative IV model where the education equation has been estimated by ordered probit. In these equations family characteristics such as parental education and occupation variables, variables identifying the type of school the individual attended, and the number of older siblings have been used as an instrument for education. We look at the robustness of our IV estimates to different identifying assumptions in more detail below.

Table 3.3: Male Returns to Education

Variable	OLS		IV			
	Coef.	(S.E.)	Coef.	(S.E.)	Coef.	(S.E)
Constant	0.197	(0.028)	0.150	(0.073)	0.152	(0.064)
Years of Education	0.114	(0.002)	0.118	(0.006)	0.117	(0.005)
Experience	0.082	(0.001)	0.081	(0.002)	0.081	(0.002)
Australian Born White	-0.003	(0.011)	-0.003	(0.011)	-0.003	(0.011)
Australian Born Non-white	0.003	(0.021)	0.004	(0.021)	0.004	(0.021)
English Good (ESL)	0.011	(0.013)	0.010	(0.013)	0.010	(0.013)
English Poor (ESL)	-0.081	(0.037)	-0.080	(0.037)	-0.080	(0.037)
Number of siblings	0.001	(0.002)	0.002	(0.002)	0.002	(0.002)
Schooling residuals			-0.005	(0.007)		
λ					-0.008	(0.010)
Number of observations	12703		12703		12703	
P-value year dummies	0.000		0.000		0.000	
P-value regional dummies	0.000		0.000		0.000	
Log Likelihood	-4158.76		-4158.49		-4158.45	
R^2	0.3424		0.3424		0.3413	

The OLS estimate of the return to education is around 11.4 per cent. The results also suggest strong returns to potential experience of around 8.2 per cent in the OLS specification. It should be pointed out that by construction an extra year of education comes at the expense of a year of potential labour market experience. Hence the actual benefit obtained from undertaking an extra year of education is given by the difference in the estimated returns to education and experience, which for the OLS specification is 3.2 per cent.

In the next column we report the results from the conventional instrumental variables estimator. This results in a slight increase in their returns to education, however, the coefficient on the residuals from the schooling equation is not significant and suggests that endogeneity may not be a problem. In the final column we present the results from our alternative IV procedure. This provides estimates of the returns to education which are again slightly above the OLS estimates but not significantly so. The coefficient on the mills ratio is negative, but insignificant. The results from this table suggest that our OLS estimates of the returns to schooling do not appear to be biased for our male sample and the coefficients from all three columns are remarkably similar.

Table 3.4: Female Returns to Education

Variable	OLS		IV			
	Coef.	(S.E.)	Coef.	(S.E.)	Coef.	(S.E)
Constant	0.187	(0.028)	0.075	(0.059)	0.026	(0.055)
Years of Education	0.111	(0.002)	0.120	(0.005)	0.124	(0.004)
Experience	0.078	(0.001)	0.077	(0.001)	0.076	(0.001)
Australian Born White	-0.014	(0.011)	-0.014	(0.011)	-0.014	(0.011)
Australian Born Non-white	-0.058	(0.020)	-0.053	(0.020)	-0.051	(0.020)
English Good (ESL)	-0.012	(0.013)	-0.014	(0.013)	-0.015	(0.013)
English Poor (ESL)	-0.042	(0.053)	-0.038	(0.053)	-0.036	(0.053)
Number of siblings	0.000	(0.002)	0.001	(0.002)	0.001	(0.002)
Schooling residuals			-0.012	(0.005)		
λ					-0.027	(0.008)
Number of observations	10859		10859		10859	
P-value year dummies	0.000		0.000		0.000	
P-value regional dummies	0.000		0.000		0.000	
Log Likelihood	-1971.94		-1969.46		-1965.68	
R^2	0.3731		0.3734		0.3738	

The corresponding results for females are reported in Table 3.4. The OLS estimate of the return to education for females is around 11.1 per cent which is slightly below that of men. The returns to potential experience are again slightly lower than for men at around 7.8 per cent. The actual benefit of undertaking an extra year of education for women is therefore very similar to the OLS estimate for men at 3.3 per cent.

The results of the IV estimation procedures, however, suggest that the returns to education are significantly underestimated by OLS and that schooling is endogenous (and/or measured with error). The corrected estimates are slightly above those obtained for men in Table 3.4 and between 8 to 12 per cent higher than the corresponding OLS estimates. The actual benefit of undertaking an extra year of education is now estimated to be around 4.3 per cent rather than 3.3 per cent.

The Returns to Highest Qualifications

We now move on to look at the returns to different qualifications. Qualifications, rather than years of education has generally been the focus of previous Australian studies of the returns to education. The results for men are presented in Table 3.5 and for women in Table 3.6. Again in these equations family characteristics, schooling variables and the number of older siblings have been used as an instrument for highest qualification.

The base group in these equations are individuals with less than 10 years of schooling and no subsequent qualifications. The OLS estimates in the first column suggest that there are significant returns to all types of qualifications. For example, for a man with a degree receives around 73 per cent more than a person in the base group. For men who completed Year 12 and subsequently undertook a diploma or certificate course, the differential is around 55 per cent. For individuals who had completed Year 12 and not subsequently completed any post school qualifications, the differential is around 35 per cent.

The results of the instrumental variables estimation given in the second column suggests that our qualification measures are endogenous and that OLS underestimate the true returns to such qualifications. The estimated differential between a person with a degree and the base group is now around

Table 3.5: Male Returns to Highest Qualifications

Variable	OLS		IV			
	Coef.	(S.E.)	Coef.	(S.E.)	Coef.	(S.E.)
Constant	1.219	(0.022)	1.179	(0.029)	1.115	(0.035)
Highest Qualification:						
Year 10	0.131	(0.016)	0.156	(0.020)	0.197	(0.024)
Year 11	0.206	(0.016)	0.248	(0.026)	0.313	(0.035)
Year 12	0.345	(0.016)	0.397	(0.030)	0.482	(0.042)
Year 12 & Tertiary	0.549	(0.019)	0.613	(0.037)	0.718	(0.052)
Degree	0.725	(0.019)	0.800	(0.042)	0.926	(0.061)
< Year 12 & Tertiary	0.287	(0.008)	0.285	(0.008)	0.284	(0.008)
Experience	0.078	(0.001)	0.078	(0.001)	0.077	(0.001)
Australian Born White	0.001	(0.011)	0.001	(0.011)	0.003	(0.011)
Australian Born Non-white	0.013	(0.022)	0.017	(0.022)	0.026	(0.022)
English Good (ESL)	0.014	(0.013)	0.009	(0.013)	-0.007	(0.015)
English Poor (ESL)	-0.079	(0.038)	-0.078	(0.038)	-0.088	(0.038)
Number of siblings	0.001	(0.002)	0.002	(0.002)	0.004	(0.002)
Mother Degree					-0.011	(0.018)
Mother Other Tertiary					-0.003	(0.010)
Father Degree					0.015	(0.015)
Father Other Tertiary					-0.003	(0.012)
Father Manager/Professional					-0.023	(0.011)
Father Salesperson/Clerk					0.005	(0.012)
Father Tradesperson					0.015	(0.010)
Father Manual					0.021	(0.010)
Mother Manager/Professional					-0.019	(0.010)
Mother Salesperson/Clerk					0.005	(0.008)
Mother Tradesperson					0.030	(0.022)
Mother Manual					-0.007	(0.010)
λ			-0.020	(0.010)	-0.049	(0.014)
Number of observations	12703		12703		12703	
P-value year dummies	0.000		0.000		0.000	
P-value regional dummies	0.000		0.000		0.000	
Log Likelihood	-4278.23		-4275.87		-4258.65	
R^2	0.3299		0.3301		0.3319	

80 per cent, an increase of 10 per cent. In the third column, we check the robustness of our IV estimates by including parental education and occupation information in our wage equation. Our identifying instruments now no longer include these variables and consist of the remaining family variables used in the reduced form equation (such as whether individuals lived with their mother only, father only or neither parent at the age of 14) as well as birth order, and schooling variables. None of these extra variables are individually significant. By including them, however, our IV estimates of the returns to qualifications increase which casts some doubts on the robustness of our IV procedure for men.

The same is not true for women, and both IV specifications are incredibly robust as seen in Table 3.6.

For women the OLS estimates of the returns to qualifications are once again significantly less that the IV estimates. The OLS estimates suggest a differential of around 69 per cent between an unqualified women and a women with a degree. The IV estimator, however, suggests that educational qualifications for women are highly endogenous and the corrected estimates are again between 15 (for Degrees) and 45 (for Year 10) per cent higher than the uncorrected estimates.

From both the male and female results it would appear that the returns to qualifications are not linear in terms of years of education. For women, for example, the return to completing Year 12 versus Year 11 is around 20 per cent, whereas the return to completing a degree versus Year 12 is only just around 14 per cent per year (assuming a degree takes three years). On the other hand, individuals who only complete Year 10 receive around 10 per cent more that those who left school before Year 10 and there is a similar difference between those who complete Year 10 and Year 11. For those who left school before Year 12 early there are significant returns to undertaking tertiary education after leaving school, particularly for men.

Table 3.6: Female Returns to Highest Qualifications

Variable	OLS		IV			
	Coef.	(S.E.)	Coef.	(S.E.)	Coef.	(S.E.)
Constant	1.233	(0.023)	1.181	(0.029)	1.169	(0.034)
Highest Qualification:						
Year 10	0.067	(0.018)	0.097	(0.021)	0.104	(0.025)
Year 11	0.152	(0.018)	0.203	(0.025)	0.216	(0.033)
Year 12	0.292	(0.018)	0.355	(0.028)	0.373	(0.040)
Year 12 & Tertiary	0.503	(0.019)	0.582	(0.032)	0.604	(0.048)
Degree	0.686	(0.021)	0.785	(0.039)	0.815	(0.060)
< Year 12 & Tertiary	0.181	(0.008)	0.177	(0.008)	0.177	(0.008)
Experience	0.077	(0.001)	0.076	(0.001)	0.076	(0.001)
Australian Born White	-0.015	(0.011)	-0.014	(0.011)	-0.014	(0.011)
Australian Born Non-white	-0.060	(0.021)	-0.053	(0.021)	-0.052	(0.021)
English Good (ESL)	-0.020	(0.013)	-0.023	(0.013)	-0.021	(0.014)
English Poor (ESL)	-0.054	(0.054)	-0.050	(0.054)	-0.050	(0.054)
Number of siblings	0.000	(0.002)	0.002	(0.002)	0.002	(0.002)
Mother Degree					-0.012	(0.015)
Mother Other Tertiary					0.007	(0.010)
Father Degree					-0.003	(0.013)
Father Other Tertiary					-0.004	(0.012)
Father Manager/Professional					-0.007	(0.010)
Father Salesperson/Clerk					-0.022	(0.013)
Father Tradesperson					-0.001	(0.010)
Father Manual					0.004	(0.010)
Mother Manager/Professional					-0.001	(0.010)
Mother Salesperson/Clerk					0.014	(0.007)
Mother Tradesperson					-0.012	(0.018)
Mother Manual					-0.015	(0.010)
λ			-0.026	(0.008)	-0.033	(0.013)
Number of observations	10859		10859		10859	
P-value year dummies	0.000		0.000		0.000	
P-value regional dummies	0.000		0.000		0.000	
Log Likelihood	-2034.46		-2029.32		-2021.74	
R^2	0.3658		0.3664		0.3673	

3.5.3 Gender Wage Differentials

In this section we look at gender wage differentials and in particular how these wage differentials vary across qualification groups. We decompose these observed wage differentials for different education groups and for the sample as a whole into differences that can be explained in terms of observed average differences in the characteristics of men and women within that education group and that attributable to women's characteristics in that group being valued differently to those of men. The results of doing this are given in Table 3.7. The estimates are based on our IV highest qualification equations which do not include parental education and occupation variables as explanatory variables.

Table 3.7: Education and Gender Wage Differentials

Highest Qualification	$(\overline{x}_m - \overline{x}_f)'\widehat{\beta}_m$		$\overline{x}'_f(\widehat{\beta}_m - \widehat{\beta}_f)$		$\widehat{g}$	
	Estimate	(S.E.)	Estimate	(S.E.)	Estimate	(S.E.)
< Year 10	0.007	(0.001)	0.010	(0.034)	0.017	(0.035)
Year 10	-0.007	(0.001)	0.093	(0.013)	0.086	(0.013)
Year 11	-0.004	(0.001)	0.049	(0.009)	0.045	(0.009)
Year 12	0.016	(0.001)	0.016	(0.010)	0.032	(0.010)
Year 12 & Tertiary	0.029	(0.001)	0.010	(0.020)	0.040	(0.020)
Degree	0.022	(0.001)	-0.006	(0.028)	0.017	(0.028)
All	-0.016	(0.002)	0.041	(0.005)	0.026	(0.004)

The results from this Table show that in terms of the observed raw differences in wages between men and women across education groups, only women in the lowest and highest educational categories receive the same wages as men. Apart from the lowest educational group, the observed wage gap decreases with education. When we decompose these gender wage differentials into our two effects we see that the relative importance of the two effects varies across educational groups. For women who only have Year 10 and Year 11 qualifications the major factor in explaining these differences would appear to differences in the price paid to observed characteristics of men and women with these qualifications. For more highly educated women, however, this would not appear to be the major source of difference in the observed wages of men and women.

Clearly the set of observed characteristics that we are conditioning on are rather limited and do not include occupation and industry variables which may be an important determinant of these differentials. Also we are using potential labour market experience, and this may be a poor proxy of actual labour market attachment, especially for women.

3.6 Conclusions

In this Chapter we have used data from the Australian Longitudinal Survey to estimate the early returns to education in Australia for the period 1985 to 1991. We find that family background characteristics are very important in explaining individual education outcomes. We find that individuals whose parents are highly educated, tend to have better educational outcomes than those whose parents are less well educated. The children of parents working in more highly skilled occupations also tend to have better educational outcomes. The region in which a person lived at the age of 14 and the type of school the person attended are also crucial in determining educational outcomes for this group of Australians born between 1960 and 1975.

But it is not purely differences across families which determine educational outcomes. Differences within families are also important. We find, for example, strong evidence that an individual's birth order (measured by the number of older siblings), controlling for family size, is a crucial factor in determining educational outcomes. In our sample educational outcomes deteriorate significantly, the more older siblings an individual has, controlling for family, year of birth and other socio-economic characteristics of parents. The number of older siblings an individual has is exogenous, given family size.

If these education outcomes are correlated with unobservable individual characteristics, then estimates of the returns to education which do not take this into account will be biased. To correct for this possible bias, we rely on instrumental variable techniques. We argue that family characteristics and order of birth can be used as instruments for education, and have no role in a wage equation which controls for educational outcomes. For men we find that the OLS and IV estimation procedures give broadly similar results for estimates of the returns to years of education. For men, OLS appears to under-estimate the return to qualifications, however, there is some question of the robustness of these results under different identifying assumptions. For women, the corrected estimates of the returns to education and highest qualifications indicate a large and significant downward bias in the OLS estimates. The corrected estimates of the returns to education for women are broadly similar to those found for men. Our female IV estimates appear robust to changes in identifying assumptions and remain almost identical when we also include parental education and occupation variables in our wage equation.

In our sample there would also appear to be significant gender wage differentials even though our sample is relatively young. The raw differentials are largest for relatively unskilled individuals, though insignificant in the very lowest education group. For individuals who have degrees there are also no significant raw gender wage differentials. We find that for relatively low skilled education groups, hardly any of the observed differential is explained by differences in average characteristics of men and women in these groups. This is not true for more highly qualified individuals.

The finding that observed family characteristics are a crucial factor in determining educational outcomes, suggests that unobserved family attributes may also be important. We look at this issue in more detail in the next Chapter when we use sibling data from the AYS and ALS. By focusing on siblings, we can specifically look at the differences between the education and earnings of brothers and sisters and this gives us a direct method of assessing the importance of unobserved family attributes when estimating the returns to education.

Appendices

A.3.1 The Age Distribution of the AYS and ALS sample

Table 3.8: Age Distribution of the ALS and AYS Sample

	Year							
Age Group	1985	1986	1987	1988	1989	1990	1991	TOTAL
16 year olds	174	4	0	0	211	155	31	575
	(30.26)	(0.70)	(0.00)	(0.00)	(36.70)	(26.96)	(5.39)	(100.00)
	[4.45]	[0.11]	[0.00]	[0.00]	[6.61]	[4.42]	[0.91]	[2.44]
17 year olds	284	332	7	0	373	316	248	1560
	(18.21)	(21.28)	(0.45)	(0.00)	(23.91)	(20.26)	(15.90)	(100.00)
	[7.26]	[9.06]	[0.22]	[0.00]	[11.69]	[9.01]	[7.24]	[6.62]
18 year olds	407	394	391	9	517	499	440	2657
	(15.32)	(14.83)	(14.72)	(0.34)	(19.46)	(18.78)	(16.56)	(100.00)
	[10.40]	[10.75]	[12.18]	[0.34]	[16.21]	[14.22]	[12.85]	[11.28]
19 year olds	446	432	397	407	452	510	506	3150
	(14.16)	(13.71)	(12.60)	(12.92)	(14.35)	(16.19)	(16.06)	(100.00)
	[11.40]	[11.79]	[12.37]	[15.34]	[14.17]	[14.53]	[14.78]	[13.37]
20 year olds	394	422	410	360	287	393	494	2760
	(14.28)	(15.29)	(14.86)	(13.04)	(10.40)	(14.24)	(17.90)	(100.00)
	[10.07]	[11.52]	[12.78]	[13.57]	[9.00]	[11.20]	[14.43]	[11.71]
21 year olds	459	373	406	386	272	345	379	2620
	(17.52)	(14.24)	(15.50)	(14.73)	(10.38)	(13.17)	(14.47)	(100.00)
	[11.73]	[10.18]	[12.65]	[14.55]	[8.53]	[9.83]	[11.07]	[11.12]
22 year olds	471	440	367	419	291	342	342	2672
	(17.63)	(16.47)	(13.74)	(15.68)	(10.89)	(12.80)	(12.80)	(100.00)
	[12.04]	[12.01]	[11.44]	[15.79]	[9.12]	[9.75]	[9.99]	[11.34]
23 year olds	484	443	422	330	275	346	330	2630
	(18.40)	(16.84)	(16.05)	(12.55)	(10.46)	(13.16)	(12.55)	(100.00.00)
	[12.37]	[12.09]	[13.15]	[12.44]	[8.62]	[9.86]	[9.64]	[11.16]
24 year olds	444	433	408	389	245	315	329	2563
	(17.32)	(16.89)	(15.92)	(15.18)	(9.56)	(12.29)	(12.84)	(100.00)
	[11.35]	[11.82]	[12.71]	[14.66]	[7.68]	[8.98]	[9.61]	[10.88]
25 year olds	350	391	401	353	267	288	325	2375
	(14.74)	(16.46)	(16.88)	(14.86)	(11.24)	(12.13)	(13.68)	(100.00)
	[8.94]	[10.67]	[12.50]	[13.31]	[8.37]	[8.21]	[9.49]	[10.08]
All Persons	3913	3664	3209	2653	3190	3509	3424	23562
	(16.61)	(15.55)	(13.62)	(11.26)	(13.54)	(14.89)	(14.53)	(100.00)
	[100.00]	[100.00]	[100.00]	[100.00]	[100.00]	[100.00]	[100.00]	[100.00]

Note: Figures in parentheses give the age distribution (per cent) across years and figures in square brackets give the age distribution [per cent] within each year.

A.3.2 Summary Statistics

Table 3.9: Summary Statistics

Variable	Males		Females	
	12703 Observations		10859 Observations	
	Mean	(Std Dev.)	Mean	(Std Dev.)
Log real hourly wage	1.810	(0.414)	1.785	(0.366)
Real hourly wage	6.637	(2.809)	6.373	(2.655)
Age	20.961	(2.574)	20.951	(2.515)
Australian Born White	0.877	(0.328)	0.884	(0.320)
Australian Born Non-white	0.020	(0.141)	0.021	(0.145)
Mother Born Australia	0.743	(0.437)	0.746	(0.436)
Father Born Australia	0.719	(0.450)	0.709	(0.454)
English Good (ESL)	0.060	(0.238)	0.061	(0.239)
English Poor (ESL)	0.007	(0.081)	0.004	(0.061)
Other City at 14	0.171	(0.377)	0.172	(0.377)
Country Town at 14	0.228	(0.419)	0.236	(0.425)
Rural Area at 14	0.100	(0.300)	0.090	(0.286)
Overseas at 14	0.011	(0.104)	0.011	(0.106)
Lived with mother only at 14	0.095	(0.293)	0.104	(0.305)
Lived with father only at 14	0.021	(0.143)	0.022	(0.148)
Lived with neither parent at 14	0.011	(0.104)	0.014	(0.117)
Mother Degree	0.044	(0.205)	0.054	(0.227)
Mother Other Tertiary	0.131	(0.337)	0.119	(0.323)
Father Degree	0.077	(0.267)	0.088	(0.283)
Father Other Tertiary	0.082	(0.275)	0.069	(0.253)
Father Manager/Professional	0.365	(0.482)	0.377	(0.485)
Father Salesperson/Clerk	0.094	(0.292)	0.087	(0.283)
Father Tradesperson	0.190	(0.392)	0.189	(0.391)
Father Manual	0.201	(0.401)	0.189	(0.391)
Mother Manager/Professional	0.142	(0.349)	0.136	(0.343)
Mother Salesperson/Clerk	0.194	(0.395)	0.213	(0.409)
Mother Tradesperson	0.017	(0.129)	0.020	(0.140)
Mother Manual	0.104	(0.305)	0.116	(0.320)
Number of siblings	2.597	(1.722)	2.521	(1.666)
Number of older siblings	1.372	(1.548)	1.372	(1.563)
School Victoria	0.245	(0.430)	0.262	(0.440)
School Queensland	0.151	(0.358)	0.157	(0.364)
School South Australia	0.086	(0.281)	0.097	(0.295)
School Western Australia	0.083	(0.276)	0.081	(0.274)
School Tasmania	0.034	(0.182)	0.037	(0.189)
School Northern Territory	0.009	(0.093)	0.009	(0.095)
School ACT	0.011	(0.105)	0.009	(0.095)
Catholic School	0.149	(0.356)	0.166	(0.372)
Private School	0.057	(0.232)	0.060	(0.238)
Experience	4.228	(2.428)	4.014	(2.455)
Years of Education	11.733	(1.626)	11.945	(1.630)
Highest Qualification:				
Degree	0.057	(0.232)	0.068	(0.252)
Year 12 & Tertiary	0.078	(0.268)	0.146	(0.353)
Year 12	0.243	(0.429)	0.267	(0.443)
Year 11	0.225	(0.418)	0.214	(0.410)
Year 10	0.346	(0.476)	0.272	(0.445)
< Year 10	0.051	(0.219)	0.033	(0.178)
< Year 12 & Tertiary	0.210	(0.407)	0.172	(0.378)

A.3.3 The Determinants of Education Outcomes

Table 3.10: The Determinants of Education Outcomes

Variable	Years of Full-time Education				Highest Qualification	
	Coef.	(S.E.)	Coef.	(S.E.)	Coef.	(S.E.)
Constant	12.275	(0.103)				
Australian Born White	0.233	(0.040)	0.156	(0.028)	0.112	(0.028)
Australian Born Non-white	-0.090	(0.078)	-0.073	(0.054)	-0.052	(0.055)
Mother Born Australia	-0.240	(0.033)	-0.167	(0.023)	-0.136	(0.023)
Father Born Australia	0.024	(0.031)	0.028	(0.021)	-0.018	(0.022)
English Good (ESL)	0.283	(0.047)	0.203	(0.033)	0.274	(0.033)
English Poor (ESL)	-0.115	(0.138)	-0.055	(0.096)	0.016	(0.097)
Other City at 14	-0.052	(0.028)	-0.039	(0.020)	-0.067	(0.020)
Country Town at 14	-0.115	(0.026)	-0.084	(0.018)	-0.120	(0.018)
Rural Area at 14	-0.081	(0.036)	-0.064	(0.025)	-0.143	(0.025)
Overseas at 14	-0.040	(0.096)	-0.024	(0.066)	-0.140	(0.067)
Lived with mother only at 14	-0.098	(0.056)	-0.102	(0.039)	-0.136	(0.040)
Lived with father only at 14	-0.015	(0.068)	-0.036	(0.047)	-0.054	(0.048)
Lived with neither parent at 14	-0.173	(0.100)	-0.185	(0.070)	-0.209	(0.071)
Mother Degree	0.474	(0.049)	0.321	(0.034)	0.326	(0.035)
Mother Other Tertiary	0.246	(0.031)	0.184	(0.022)	0.187	(0.022)
Father Degree	0.468	(0.040)	0.296	(0.028)	0.392	(0.028)
Father Other Tertiary	0.350	(0.038)	0.237	(0.027)	0.197	(0.027)
Father Manager/Professional	0.263	(0.051)	0.178	(0.035)	0.172	(0.036)
Father Salesperson/Clerk	0.210	(0.057)	0.147	(0.040)	0.166	(0.041)
Father Tradesperson	0.064	(0.052)	0.039	(0.036)	0.006	(0.037)
Father Manual	-0.118	(0.052)	-0.103	(0.036)	-0.148	(0.037)
Mother Manager/Professional	0.124	(0.031)	0.093	(0.022)	0.137	(0.022)
Mother Salesperson/Clerk	0.038	(0.026)	0.033	(0.018)	0.046	(0.019)
Mother Tradesperson	-0.005	(0.073)	-0.003	(0.051)	-0.006	(0.052)
Mother Manual	-0.077	(0.034)	-0.054	(0.023)	-0.039	(0.024)
Number of siblings	-0.047	(0.008)	-0.036	(0.006)	-0.031	(0.006)
Number of older siblings	-0.053	(0.009)	-0.037	(0.006)	-0.039	(0.006)
School Victoria	0.092	(0.026)	0.076	(0.018)	0.241	(0.018)
School Queensland	0.279	(0.030)	0.206	(0.021)	0.310	(0.021)
School South Australia	0.410	(0.037)	0.309	(0.025)	0.425	(0.026)
School Western Australia	0.011	(0.038)	0.024	(0.027)	0.058	(0.027)
School Tasmania	-0.448	(0.054)	-0.328	(0.038)	-0.259	(0.039)
School Northern Territory	0.201	(0.104)	0.172	(0.072)	0.212	(0.073)
School ACT	0.511	(0.098)	0.381	(0.068)	0.643	(0.069)
Catholic School	0.373	(0.027)	0.268	(0.019)	0.259	(0.019)
Private School	0.800	(0.043)	0.534	(0.030)	0.624	(0.031)
Male	-0.196	(0.019)	-0.141	(0.014)	-0.246	(0.014)
μ_1			-3.020	(0.078)	-1.984	(0.074)
μ_2			-2.251	(0.073)	-0.515	(0.073)
μ_3			-1.060	(0.072)	0.110	(0.073)
μ_4			-0.500	(0.072)	0.958	(0.073)
μ_5			0.523	(0.072)	1.615	(0.074)
μ_6			0.781	(0.072)		
μ_7			1.273	(0.072)		
μ_8			2.140	(0.074)		
μ_9			2.464	(0.077)		
Number of observations	23562		23562		23562	
P-value Year Born Dummies	0.000		0.000		0.000	
Log Likelihood	-42682.05		-39803.64		-35347.09	
(Pseudo) R^2	0.1759		0.0528		0.0585	

Chapter 4

Education, Family Attributes and the Earnings of Siblings

4.1 Introduction

Estimates of the returns to education which do not take into account correlations between unobserved individual characteristics and education can be biased. In the previous Chapter we used data from a random sample of individuals aged between 16 and 25, and used instrumental variables techniques to try and correct for these biases. We found that our corrected estimates of the returns to education were significantly higher than our uncorrected estimates for women, though broadly similar for men. In this Chapter, we estimate "within family" estimates of the returns to education using a sample of siblings from the AYS and ALS data used in the previous Chapter. This kind of data potentially allows us to eliminate any biases caused by correlations of education with unobserved family attributes. Such a model implicitly assumes that the most important component of unobserved correlated effects pertain to the family rather than individual effects which might vary within families. However, the birth order effects we found in the last Chapter suggest that correlated family effects might not be the whole story. As we saw in Chapter 2, early within family studies such as the Australian study conducted by Bradbury, McRae and Woyzbun [40] and others reviewed by Griliches [82] tended to find that a major part of the estimated returns to education were in fact due to correlation between schooling and unmeasured family components. More recent studies, such as those by Ashenfelter and Zimmerman [12] and Ashenfelter and Krueger [11] have cast doubt on these earlier findings and argue that once account is taken of issues such as measurement error, the within family estimates are similar or larger than OLS estimates of the returns to education.

In this Chapter we use a sibling sub-sample from the Australian Longitudinal Survey (ALS) and Australian Youth Survey (AYS) data used in the previous Chapter and compare these within family estimates with those obtained previously using OLS and IV techniques. The surveys are based on a sample of dwellings and all individuals in the given age range living in these dwellings were included in the sample. This means that the sample includes a large number of siblings.

The advantage of using sibling data is that it allows one to obtain a corrected estimate of the return to education, by either looking at the differences between siblings education and earnings or by proxying the family effect using data from both siblings. These estimates should be free from biases caused the correlation of education with unobserved (as well as observed) family attributes. The use of within family estimation techniques are, however, not entirely problem free. In particular, if fixed effect methods are used, the statistical problems associated with measurement error tend to be accentuated. Also these models assume that these unobserved family attributes affect older and younger siblings in identical ways. If this assumption is not valid, then the estimates may still be biased.

We find that the estimated returns to education for our sibling sample using conventional cross sectional approaches are, for the most part, similar to those found for the whole sample in the previous Chapter. The results we obtain indicate that for the whole sample, within family estimates of the returns to education and qualifications are below those obtained using conventional OLS methods. It is clear, however, that one should treat brother, sister and brother and sister pairs separately. For brothers, the within family estimates are generally above OLS estimates, whereas for sisters they are the same (proxy) or below (fixed effect) conventional estimates. In mixed sibling pairs the within family estimates are always below conventional estimates. Our results for brothers are broadly consistent with the recent US study by Ashenfelter and Krueger [11] using a sample of male twins. Their estimates also corrected for measurement error. No attempt has been made to correct for measurement error in our study because of the lack of available instruments, and this may mean that our estimates and in particular our fixed effect estimates may be downward biased. We also look at how reasonable the assumption is that unobserved family characteristics affect older and younger sibling in identical manners. We do this by seeing whether this assumption holds for observed family attributes that we have in our data.

In section 2 we look at the sibling sub-sample and compare its characteristics to that of the whole ALS and AYS sample used in the previous Chapter. In section 3 we outline our estimation methodology. This draws on the earlier work of Ashenfelter and Krueger [11] and Ashenfelter and Zimmerman [12]. In section 4 we report the results of our analysis. In the first part of the section we replicate the instrumental variable methodology used in the previous chapter to see if the results obtained there are carried through into our sibling sample. We then see how these estimates compare to within family estimates of the returns to education. Conclusions are discussed in Section 5.

4.2 The Representativeness of the Sibling Sample

The variables used in this Chapter are constructed in an identical manner to the variables used in the previous Chapter. In this chapter, however, we restrict ourselves to pairs of siblings who have both completed full-time education and who are both employed in the year of the survey. If there are more than two siblings in the sample we only include the two oldest siblings in our sample. This leaves us with a final sample 1964 males and 1388 females constituting 1676 sibling pairs. This comprises of 598 male sibling pairs, 310 female sibling pairs and 768 mixed sibling pairs.

The age distribution of our sibling sub-sample is given in Table 4.22 of Appendix A.4.1 and full summary statistics for the sample in Table 4.23 of Appendix A.4.2. Table 4.1 provides descriptive statistics for some of the key variables used in our analysis and compares these with the summary statistics for the whole AYS and ALS sample which was used in the previous Chapter.

Table 4.1: Key Summary Statistics

	Sibling Sample		Complete Sample	
Variable	Mean	(Std Dev.)	Mean	(Std Dev)
Years of Education	11.84	(1.57)	11.83	(1.63)
Highest Qualification:				
Degree	0.06	(0.23)	0.06	(0.24)
Year 12 & Diploma	0.11	(0.31)	0.11	(0.31)
Year 12	0.25	(0.43)	0.25	(0.44)
Year 11	0.22	(0.42)	0.22	(0.41)
Year 10	0.32	(0.47)	0.31	(0.46)
< Year 10	0.03	(0.18)	0.04	(0.20)
< Year 12 & Diploma	0.21	(0.40)	0.19	(0.39)
Hourly Wage ($A)	6.51	(2.65)	6.52	(2.74)
Age	20.86	(2.41)	20.96	(2.55)
Experience	4.02	(2.24)	4.13	(2.44)
No. of Siblings	2.59	(1.44)	2.56	(1.70)
No. of Older Siblings	1.26	(1.32)	1.37	(1.56)
Male	0.59	(0.49)	0.54	(0.50)
Mother Degree	0.03	(0.18)	0.05	(0.22)
Mother Other Tertiary	0.12	(0.33)	0.13	(0.33)
Father Degree	0.09	(0.29)	0.08	(0.27)
Father Other Tertiary	0.08	(0.26)	0.08	(0.27)
Sample Size	3352		23562	

We see that mean years of education for both samples are very similar as are the highest qualification variables. The major difference between the two samples is the proportion of men. The over-representation of males in the sibling sample presumably reflects the fact that men tend to stay at home with their parents longer than women. In order to be included in our sample, both siblings had to be living together at the time of the initial survey in 1985 for the ALS or 1989, 1990 or 1991 for the AYS.

In Table 4.23 we look at the differences in the mean characteristics of the elder and younger siblings in our sample. The average age difference between siblings is just over two years. We also see that the older siblings in our sample have on average completed just over half a year more education than the younger siblings in our pairs. The older siblings also have higher average hourly wages and more labour market experience. We also see that men are very over-represented among the older sibling group as well as in the sibling sample as a whole.

Table 4.2: Key Summary Statistics for Each Sibling

	Elder Sibling		Younger Sibling	
Variable	Mean	(Std Dev.)	Mean	(Std Dev)
Years of Education	12.14	(1.66)	11.54	(1.42)
Highest Qualification:				
Degree	0.08	(0.27)	0.04	(0.19)
Year 12 & Diploma	0.13	(0.34)	0.09	(0.28)
Year 12	0.24	(0.43)	0.26	(0.44)
Year 11	0.22	(0.41)	0.23	(0.42)
Year 10	0.29	(0.46)	0.35	(0.48)
< Year 10	0.03	(0.17)	0.03	(0.18)
< Year 12 & Diploma	0.24	(0.43)	0.17	(0.38)
Hourly Wage ($A)	7.06	(2.79)	5.96	(2.39)
Age	21.95	(2.20)	19.77	(2.11)
Experience	4.81	(2.27)	3.23	(1.90)
No. of Siblings	2.59	(1.44)	2.59	(1.44)
No. of Older Siblings	0.73	(1.20)	1.79	(1.23)
Male	0.61	(0.49)	0.57	(0.50)
Mother Degree	0.03	(0.17)	0.03	(0.18)
Mother Other Tertiary	0.12	(0.33)	0.12	(0.33)
Father Degree	0.09	(0.29)	0.09	(0.29)
Father Other Tertiary	0.08	(0.27)	0.07	(0.26)
Sample Size	1676		1676	

4.3 Methodology

Following the approach outlined in the last chapter we begin by using a two equation system of the form

$$w_i = s_i\beta_1 + X_i'\beta_{23} + u_i \tag{4.1}$$

$$s_i = Z_i'\gamma + v_i \tag{4.2}$$

where s_i is years of schooling (full-time years of education), w_i is the log real hourly wage rate, X_i and Z_i are vectors of exogenous observed individual characteristics, β_1 is the return to education and u_i and v_i are a pair of residuals. OLS estimation of equation (4.1) gives rise to a unbiased estimate of the return to education if u_i and v_i are uncorrelated, that is if s_i is exogenous ($E(s_i u_i) = 0$).

In the previous Chapter we used instrumental variable techniques to obtain consistent estimates of the returns to education. In this chapter we compare this methodology with "within family" estimation procedures. We use two approaches when estimating within family returns to education. The first involves proxying the family effect and estimating the selection effect explicitly, whereas the second involves using a fixed effect approach which eliminates the endogeneity bias associated with unobserved family effects by exploiting the differences between siblings levels of schooling and earnings. Following Ashenfelter and Krueger [11] and Ashenfelter and Zimmerman [12] we let w_{1i} and w_{2i} be the logarithm of the hourly wage rate of the siblings in the ith pair. We assume that X_i in equation (4.1) can be divided into observable variables which vary by family X_{fi} and observable components which vary by individual persons, X_{1i} and X_{2i}. Clearly schooling s_i will also vary by individual, s_{1i} and s_{2i}. Similarly we assume we can split the unobservable individual components in equation (4.1) as u_{1i} and u_{2i}. This implies that

$$w_{1i} = s_{1i}\beta_1 + X_{1i}'\beta_2 + X_{fi}'\beta_3 + f_i + \eta_{1i} \tag{4.3}$$

$$w_{2i} = s_{2i}\beta_1 + X'_{2i}\beta_2 + X'_{fi}\beta_3 + f_i + \eta_{2i} \tag{4.4}$$

where it is assumed that the equations are identical for the two siblings and where f_i is interpreted as an unobservable fixed component that varies by family where $u_{1i} = f_i + \eta_{1i}$ and $u_{2i} = f_i + \eta_{2i}$. We now assume that the correlation between this family effect and the observables for each sibling are the same and can be proxied by

$$f_i = (X_{1i} + X_{2i})'\psi + (s_{1i} + s_{2i})\theta + X'_{fi}\delta + \mu_i \tag{4.5}$$

where μ_i is uncorrelated with all the right hand side variables in equation (4.5). The coefficients ψ and θ measure the "selection effect" relating earnings and the observables, while the coefficients β_1, β_2 and β_3, measure the selection corrected or the structural effect of the observables on earnings. Our sibling data therefore makes it possible to measure the selection effect of the rate of return to schooling (θ), and the selection corrected return to schooling (β_1). By substituting equation (4.5) into equations (4.4) and (4.3) we get the reduced form for the model

$$w_{1i} = s_{1i}(\beta_1+\theta)+s_{2i}\theta+X'_{1i}(\beta_2+\psi)+X'_{2i}\psi+X'_{fi}(\beta_3+\delta)+\mu_i+\eta_{1i} \tag{4.6}$$

$$w_{2i} = s_{1i}\theta+s_{2i}(\beta_1+\theta)+X'_{1i}\beta_2+X'_{2i}(\beta_2+\psi)+X'_{fi}(\beta_3+\delta)+\mu_i+\eta_{2i} \tag{4.7}$$

which can be estimated by stacking the two equations and estimating them by OLS or GLS. GLS is optimal in this framework because of the cross equation restrictions on the coefficients and because it also provided the correct standard errors for the estimated coefficients. This framework suggests that both sibling's education levels (and any other variable that varies by sibling) may enter into both wage equations because of the correlations between the family effect and schooling levels. In this setup, the coefficients on the variables that differ by siblings ($\beta_1$and β_2) are identified, however, the coefficients on the variables that only differ across families (β_3) are not identified. The difference between equations (4.4) and (4.3) (or (4.6) and (4.7)) is given by

$$w_{1i} - w_{2i} = (s_{1i} - s_{2i})\beta_1 + (X_{1i} - X_{2i})'\beta_2 + (\eta_{1i} - \eta_{2i}) \tag{4.8}$$

where in this formulation the unobserved family effect f_i as well as observed family effects have been eliminated. Clearly we can test the validity of this assumption with respect to observed family attributes. If these family attributes affect the wages of older and younger sons identically then if we enter these variables (as levels) in the fixed effect equation they should be insignificant. We look at this question at the end of this Chapter. OLS estimation of equation (4.8) gives the traditional "fixed effects" estimator. Hence we have two approaches with this sort of data. We can proxy the family effect and use equations (4.6) and (4.7) to estimated the selection effect explicitly and then subtract this to obtain the selection corrected estimates of the returns to schooling. Alternatively we can eliminate the selection term by differencing and estimate the selection corrected return to schooling for OLS estimation of equation (4.8).

As we saw in Chapter 2, the fixed effect estimator has the disadvantage of introducing far greater measurement error bias. To deal with the problem of measurement error and/or the possibility that the endogeneity of schooling arises not purely because of unobserved family effects, we once again need to rely on instrumental variables techniques. In particular, to consistently estimate the returns to education we require at least one instrument for schooling in equations (4.6) and (4.7) or the difference in siblings schooling for equation (4.8). Ashenfelter and Krueger [11] used independent measures of schooling provided by the other twin in their study. The problem for us here, is that the instrument set used in the previous Chapter consisted almost entirely of family background variables and these clearly are not useful in a within family estimation procedure since they will tend not to vary between siblings. We must bear in mind that our within family estimates may be downward biased, especially our fixed effects estimates, due to measurement error.[1].

4.4 Results

4.4.1 Cross Sectional Estimates of the Returns to Education

Determinants of Education Outcomes

We follow the exact methodology of the previous Chapter and look first look at the determinants of education outcomes for our sibling sample. The results for men are given in Table 4.3 and for women in Table 4.4. The results for the whole sample are given in Table 4.24 in Appendix A.4.3.

Once again all three equations in Table 4.3 give very similar results as to the determinants of educational outcomes for men and these are broadly similar to the results of the previous Chapter. Men whose parents have a degree have significantly better education outcomes than men from less educated parents. It is also true that sons whose fathers work in more highly skilled occupations do significantly better than sons whose fathers work in relatively unskilled jobs. There is some weak evidence that sons of mothers in professional occupations when the child was 14 also do better. Men who lived with their mother only at 14, also tend to have lower educational attainment, though this result does not hold in all specifications. Men from Australian born fathers, however, now appear to do significantly worse than men with father's born overseas. This is the opposite to what was found for the whole

[1]Some of the family variables also do vary between siblings, simply because of age differences. Most of the family background variables relate to when the individual was fourteen and if family circumstances changed between the time the elder sibling and younger sibling turned 14, then differences will arise. There are also differences between some siblings in the types of schools they attended. In our sibling sample, we also include sibling's education in our education equations. This will act as an instrument in wage equations which do not include sibling variables as explanatory variables. Birth order varies by sibling, but because the youngest sibling is by definition, going to be further down the birth order, it is impossible to identify birth order effects, from age effects.

Table 4.3: The Determinants of Male Education Outcomes

Variable	Years of Full-time Education				Highest Qualification	
	Coef.	(S.E.)	Coef.	(S.E.)	Coef.	(S.E.)
Constant	11.973	(0.396)				
Australian Born White	0.418	(0.134)	0.312	(0.104)	0.343	(0.106)
Australian Born Non-white	-0.036	(0.344)	0.002	(0.266)	0.203	(0.270)
Mother Born Australia	-0.010	(0.108)	0.000	(0.083)	0.025	(0.084)
Father Born Australia	-0.213	(0.103)	-0.166	(0.079)	-0.349	(0.081)
English Good (ESL)	-0.060	(0.148)	-0.068	(0.114)	0.027	(0.116)
English Poor (ESL)	-0.728	(0.569)	-0.727	(0.445)	-1.536	(0.501)
Other City at 14	0.043	(0.091)	0.029	(0.070)	-0.016	(0.072)
Country Town at 14	-0.322	(0.090)	-0.246	(0.070)	-0.276	(0.072)
Rural Area at 14	0.003	(0.127)	-0.009	(0.099)	-0.143	(0.101)
Overseas at 14	-0.188	(0.353)	-0.185	(0.274)	-0.716	(0.292)
Lived with mother only at 14	-0.288	(0.201)	-0.305	(0.157)	-0.182	(0.160)
Lived with father only at 14	-0.039	(0.490)	0.072	(0.381)	-0.149	(0.388)
Lived with neither parent at 14	-0.017	(0.634)	-0.055	(0.492)	0.382	(0.491)
Mother Degree	0.400	(0.202)	0.280	(0.156)	0.399	(0.159)
Mother Other Tertiary	0.054	(0.098)	0.050	(0.075)	0.011	(0.077)
Father Degree	0.605	(0.123)	0.434	(0.095)	0.629	(0.097)
Father Other Tertiary	0.179	(0.126)	0.151	(0.097)	0.078	(0.099)
Father Manager/Professional	0.381	(0.159)	0.282	(0.124)	0.360	(0.126)
Father Salesperson/Clerk	0.264	(0.180)	0.199	(0.140)	0.395	(0.143)
Father Tradesperson	0.401	(0.164)	0.283	(0.127)	0.322	(0.130)
Father Manual	0.153	(0.162)	0.107	(0.126)	0.085	(0.129)
Mother Manager/Professional	0.117	(0.107)	0.103	(0.083)	0.157	(0.085)
Mother Salesperson/Clerk	0.008	(0.086)	0.029	(0.066)	-0.040	(0.068)
Mother Tradesperson	0.043	(0.239)	0.109	(0.185)	0.187	(0.186)
Mother Manual	0.022	(0.104)	0.016	(0.081)	0.039	(0.082)
Number of siblings	-0.069	(0.033)	-0.050	(0.025)	-0.048	(0.026)
Number of older siblings	-0.072	(0.035)	-0.062	(0.027)	-0.066	(0.028)
School Victoria	-0.080	(0.083)	-0.023	(0.064)	0.182	(0.065)
School Queensland	0.182	(0.100)	0.182	(0.078)	0.308	(0.080)
School South Australia	0.624	(0.141)	0.496	(0.108)	0.728	(0.110)
School Western Australia	0.044	(0.122)	0.069	(0.094)	-0.056	(0.096)
School Tasmania	-0.841	(0.225)	-0.653	(0.177)	-0.587	(0.186)
School Northern Territory	0.110	(0.419)	0.170	(0.320)	-0.527	(0.334)
School ACT	0.964	(0.234)	0.752	(0.181)	1.083	(0.182)
Catholic School	0.368	(0.080)	0.287	(0.062)	0.219	(0.063)
Private School	0.634	(0.143)	0.510	(0.110)	0.717	(0.112)
μ_1			-3.238	(0.335)	-2.368	(0.320)
μ_2			-2.443	(0.314)	-0.550	(0.315)
μ_3			-0.985	(0.308)	0.138	(0.315)
μ_4			-0.431	(0.307)	1.073	(0.316)
μ_5			0.694	(0.308)	1.624	(0.317)
μ_6			0.996	(0.308)		
μ_7			1.562	(0.310)		
μ_8			2.638	(0.324)		
μ_9			3.405	(0.392)		
Number of observations	1964		1964		1964	
P-value Year Born Dummies	0.000		0.000		0.000	
Log Likelihood	-3349.37		-3093.39		-2707.87	
(Pseudo) R^2	0.2478		0.0832		0.0874	

sample in the previous Chapter.

Men who lived in a country town or a rural area when aged 14 do significantly worse than men who lived in cities when they were aged 14, though again this varies across specifications. White Australian born men do significantly better than non-white Australian born men and overseas born men. Individual's whose first language was not English also appear to have worse educational outcomes, though these estimates are imprecisely determined.

The State in which the man last went to school and the type of school he went to, are again important in determining educational outcomes. It is also clear that family composition and order of birth are both still very important determinants of educational outcomes for men. Once again. educational outcomes are significantly worse for men who come from large families. Moreover, given family size, men with more older siblings do significantly worse than those with less older siblings. We must be careful about how we interpret this birth order effect in our sibling sample as birth order is no longer independent of age. By definition the older siblings in our sample will have less older siblings than the younger sibling and it is impossible to identify these age effects from birth order effects in such a sample.

The results for women are also broadly consistent with those reported for the whole sample of women in the previous Chapter. Parent's education is again crucial, as well as mother's and father's occupational status. White Australian born women also do significantly better than women for who this is not true. Regional and school variables are also very important. For women in this sibling sample, number of siblings is again not significant as was the case for the whole sample , but number of older siblings is once again negative and significant. Again caution must be exercised in interpreting this birth order effect.

In Table 4.24 of Appendix A.4.3 we report the results for the male and female sample as a whole. The results from this table suggest that the educational outcomes of women are significantly higher than those of men in

Table 4.4: The Determinants of Female Education Outcomes

Variable	Years of Full-time Education				Highest Qualification	
	Coef.	(S.E.)	Coef.	(S.E.)	Coef.	(S.E.)
Constant	11.729	(0.597)				
Australian Born White	0.312	(0.169)	0.257	(0.126)	0.281	(0.128)
Australian Born Non-white	-0.461	(0.499)	-0.361	(0.371)	-0.278	(0.378)
Mother Born Australia	-0.020	(0.148)	-0.028	(0.110)	-0.046	(0.112)
Father Born Australia	-0.313	(0.125)	-0.202	(0.094)	-0.163	(0.095)
English Good (ESL)	0.257	(0.197)	0.237	(0.146)	0.225	(0.148)
English Poor (ESL)	0.589	(0.520)	0.586	(0.389)	0.450	(0.386)
Other City at 14	-0.068	(0.116)	-0.054	(0.086)	-0.170	(0.088)
Country Town at 14	-0.426	(0.111)	-0.307	(0.083)	-0.413	(0.084)
Rural Area at 14	0.068	(0.182)	0.063	(0.135)	0.086	(0.137)
Overseas at 14	0.218	(0.408)	0.151	(0.303)	-0.645	(0.309)
Lived with mother only at 14	0.468	(0.254)	0.256	(0.190)	-0.069	(0.192)
Lived with father only at 14	0.787	(0.340)	0.539	(0.251)	0.840	(0.263)
Lived with neither parent at 14	-0.271	(0.732)	-0.150	(0.553)	0.103	(0.552)
Mother Degree	0.767	(0.221)	0.607	(0.165)	0.555	(0.167)
Mother Other Tertiary	0.217	(0.137)	0.183	(0.102)	0.315	(0.104)
Father Degree	0.849	(0.151)	0.566	(0.114)	0.574	(0.115)
Father Other Tertiary	0.980	(0.158)	0.703	(0.118)	0.749	(0.121)
Father Manager/Professional	0.504	(0.210)	0.350	(0.157)	0.197	(0.158)
Father Salesperson/Clerk	0.434	(0.239)	0.258	(0.179)	0.101	(0.181)
Father Tradesperson	0.666	(0.219)	0.476	(0.164)	0.356	(0.165)
Father Manual	0.602	(0.220)	0.414	(0.165)	0.213	(0.166)
Mother Manager/Professional	0.341	(0.134)	0.266	(0.100)	0.245	(0.101)
Mother Salesperson/Clerk	0.024	(0.101)	0.059	(0.075)	0.139	(0.076)
Mother Tradesperson	-0.091	(0.291)	-0.093	(0.217)	-0.008	(0.219)
Mother Manual	-0.340	(0.131)	-0.283	(0.098)	-0.275	(0.099)
Number of siblings	0.005	(0.039)	0.000	(0.029)	0.001	(0.030)
Number of older siblings	-0.093	(0.042)	-0.056	(0.032)	-0.055	(0.032)
School Victoria	0.063	(0.104)	0.097	(0.078)	0.217	(0.079)
School Queensland	0.857	(0.128)	0.672	(0.096)	0.736	(0.098)
School South Australia	0.208	(0.158)	0.266	(0.118)	0.476	(0.119)
School Western Australia	0.295	(0.160)	0.263	(0.119)	0.023	(0.121)
School Tasmania	-0.954	(0.201)	-0.742	(0.151)	-0.609	(0.154)
School Northern Territory	0.488	(0.350)	0.473	(0.261)	0.540	(0.261)
School ACT	-0.081	(1.423)	0.181	(1.075)	0.245	(1.059)
Catholic School	0.154	(0.102)	0.135	(0.076)	0.120	(0.077)
Private School	1.098	(0.178)	0.788	(0.133)	0.627	(0.136)
μ_1			-2.749	(0.464)	-1.689	(0.460)
μ_2			-2.116	(0.452)	-0.206	(0.456)
μ_3			-0.959	(0.448)	0.471	(0.456)
μ_4			-0.241	(0.447)	1.361	(0.458)
μ_5			0.844	(0.448)	2.287	(0.460)
μ_6			1.111	(0.448)		
μ_7			1.744	(0.449)		
μ_8			2.686	(0.457)		
μ_9			3.088	(0.467)		
Number of observations	1388		1388		1388	
P-value Year Born Dummies	0.000		0.000		0.000	
Log Likelihood	-2400.27		-2259.20		-2022.90	
(Pseudo) R^2	0.2861		0.0902		0.0964	

our sibling sample and this once again is consistent with our findings for the whole sample.

Cross-sectional Returns to Years of Education

Table 4.5 reports the results for men in our sibling sample of cross-sectional OLS and IV estimation procedures. Our instruments for education are once again the same family background variables, schooling variables and also include the number of older siblings.

Table 4.5: Cross-sectional Estimates of Male Returns to Education

Variable	OLS		IV			
	Coef.	(S.E.)	Coef.	(S.E.)	Coef.	(S.E)
Constant	0.095	(0.068)	0.209	(0.154)	0.193	(0.138)
Years of Education	0.128	(0.005)	0.118	(0.013)	0.119	(0.012)
Experience	0.081	(0.003)	0.083	(0.004)	0.083	(0.004)
Australian Born White	-0.016	(0.028)	-0.012	(0.028)	-0.013	(0.028)
Australian Born Non-white	0.035	(0.051)	0.037	(0.052)	0.037	(0.052)
English Good (ESL)	-0.065	(0.032)	-0.066	(0.032)	-0.066	(0.032)
English Poor (ESL)	-0.047	(0.124)	-0.055	(0.125)	-0.054	(0.125)
Number of siblings	-0.002	(0.006)	-0.003	(0.006)	-0.003	(0.006)
Schooling residuals			0.014	(0.017)		
λ					0.017	(0.021)
Number of observations	1964		1964		1964	
P-value year dummies	0.000		0.000		0.000	
P-value regional dummies	0.000		0.000		0.000	
Log Likelihood	-521.86		-521.47		-521.51	
R^2	0.3777		0.3780		0.3780	

The OLS estimate of the return to education for men in our sibling sample around 12.8 per cent. This compares with our estimate of 11.4 per cent for the whole male sample. Once again there are strong returns to experience and these are the same as those found for the sample as a whole. The IV results are almost identical to those found in the previous Chapter, however, there is no evidence that years of schooling is endogenous on the basis of Hausman t tests. The overall results suggest that the average return to years of education for this group may be slightly higher than we saw for the whole sample.

The corresponding results for females are reported in Table 4.6. The OLS estimate of the return to education for females in our sibling sub-sample is

Table 4.6: Cross-sectional Estimates of Female Returns to Education

Variable	OLS		IV			
	Coef.	(S.E.)	Coef.	(S.E.)	Coef.	(S.E)
Constant	0.197	(0.078)	0.076	(0.135)	0.071	(0.132)
Years of Education	0.115	(0.006)	0.126	(0.011)	0.126	(0.011)
Experience	0.076	(0.004)	0.074	(0.004)	0.074	(0.004)
Australian Born White	-0.042	(0.029)	-0.041	(0.029)	-0.041	(0.029)
Australian Born Non-white	-0.237	(0.047)	-0.224	(0.047)	-0.224	(0.047)
English Good (ESL)	-0.063	(0.037)	-0.064	(0.037)	-0.064	(0.037)
English Poor (ESL)	-0.227	(0.055)	-0.231	(0.056)	-0.231	(0.056)
Number of siblings	-0.004	(0.005)	-0.004	(0.005)	-0.003	(0.005)
Schooling residuals			-0.015	(0.013)		
λ					-0.023	(0.018)
Number of observations	1388		1388		1388	
P-value year dummies	0.000		0.000		0.000	
P-value regional dummies	0.001		0.001		0.001	
Log Likelihood	-199.21		-198.34		-198.18	
R^2	0.3734		0.3742		0.3743	

around 11.5 per cent compared to around 11.1 per cent for the whole AYS and ALS sample. The results of the IV estimation procedures once again suggest that the returns to education are underestimated by OLS. The corrected estimates suggest that the return is around 12.6 per cent which is broadly comparable to the IV results obtained in the last Chapter of between 12.0 and 12.4 per cent.

Cross-sectional Returns to Highest Qualifications

We now once again move on to look at the returns to different qualifications rather than years of education again using the same methodology of the previous Chapter. It was clear from the previous Chapter that the returns to education were not linear in terms of years of education and this is specifically allowed for when we instead look at the returns to highest qualification. The results for men are presented in Table 4.7 and for women in Table 4.8.

The OLS estimates once again suggest that there are significant returns to all types of qualifications for men in our sibling sample. Once again a man with a degree receives about 72 per cent more than an unqualified man . This OLS estimate is almost identical to that obtained in the previous Chapter. The results of our instrumental variables estimation suggests that OLS esti-

Table 4.7: Cross-sectional Male Returns to Highest Qualifications

Variable	OLS		IV			
	Coef.	(S.E.)	Coef.	(S.E.)	Coef.	(S.E.)
Constant	1.272	(0.062)	1.317	(0.074)	1.342	(0.080)
Highest Qualification:						
Year 10	0.086	(0.052)	0.054	(0.059)	0.007	(0.062)
Year 11	0.186	(0.053)	0.135	(0.071)	0.054	(0.079)
Year 12	0.354	(0.052)	0.292	(0.078)	0.202	(0.091)
Year 12 & Tertiary	0.613	(0.056)	0.537	(0.090)	0.431	(0.107)
Degree	0.721	(0.057)	0.634	(0.101)	0.493	(0.124)
$<$ Year 12 & Tertiary	0.323	(0.020)	0.327	(0.020)	0.338	(0.020)
Experience	0.078	(0.004)	0.079	(0.004)	0.082	(0.004)
Australian Born White	-0.004	(0.028)	-0.002	(0.028)	0.019	(0.028)
Australian Born Non-white	0.054	(0.052)	0.059	(0.053)	0.109	(0.059)
English Good (ESL)	-0.046	(0.033)	-0.045	(0.033)	-0.060	(0.034)
English Poor (ESL)	-0.069	(0.123)	-0.093	(0.124)	-0.142	(0.117)
Number of siblings	-0.001	(0.006)	-0.002	(0.006)	-0.005	(0.006)
Mother Degree					0.164	(0.061)
Mother Other Tertiary					0.049	(0.022)
Father Degree					0.079	(0.033)
Father Other Tertiary					-0.013	(0.033)
Father Manager/Professional					-0.013	(0.026)
Father Salesperson/Clerk					-0.028	(0.031)
Father Tradesperson					0.043	(0.029)
Father Manual					0.043	(0.027)
Mother Manager/Professional					-0.074	(0.030)
Mother Salesperson/Clerk					-0.009	(0.020)
Mother Tradesperson					0.063	(0.049)
Mother Manual					0.031	(0.021)
λ			0.023	(0.022)	0.054	(0.028)
Number of observations	1964		1964		1964	
P-value year dummies	0.000		0.000		0.000	
P-value regional dummies	0.000		0.000		0.000	
Log Likelihood	-535.45		-534.78		-509.37	
R^2	0.3691		0.3695		0.3856	

mates may overestimate the true returns to education which is opposite to what was found in the previous Chapter. Our male IV results for highest qualifications were not very robust to specification changes and robustness is once again an issue in these estimates when we compare the IV results in the second column with those in the third column when we control for parent's education and occupation.

The results for females in our sibling sample are given in Table 4.8.

Table 4.8: Cross-sectional Female Returns to Highest Qualifications

Variable	OLS		IV			
	Coef.	(S.E.)	Coef.	(S.E.)	Coef.	(S.E.)
Constant	1.279	(0.054)	1.229	(0.065)	1.189	(0.074)
Highest Qualification:						
Year 10	0.073	(0.037)	0.107	(0.044)	0.127	(0.050)
Year 11	0.179	(0.038)	0.233	(0.053)	0.260	(0.068)
Year 12	0.330	(0.038)	0.398	(0.060)	0.437	(0.081)
Year 12 & Tertiary	0.532	(0.042)	0.612	(0.069)	0.661	(0.098)
Degree	0.706	(0.050)	0.808	(0.089)	0.875	(0.125)
< Year 12 & Tertiary	0.194	(0.022)	0.190	(0.023)	0.188	(0.023)
Experience	0.075	(0.004)	0.074	(0.004)	0.074	(0.004)
Australian Born White	-0.064	(0.029)	-0.066	(0.029)	-0.065	(0.029)
Australian Born Non-white	-0.251	(0.048)	-0.240	(0.048)	-0.249	(0.053)
English Good (ESL)	-0.071	(0.038)	-0.073	(0.038)	-0.075	(0.041)
English Poor (ESL)	-0.212	(0.074)	-0.218	(0.076)	-0.230	(0.082)
Number of siblings	-0.004	(0.005)	-0.003	(0.005)	-0.001	(0.005)
Mother Degree					0.016	(0.044)
Mother Other Tertiary					0.054	(0.028)
Father Degree					-0.003	(0.032)
Father Other Tertiary					-0.055	(0.038)
Father Manager/Professional					-0.019	(0.028)
Father Salesperson/Clerk					0.013	(0.039)
Father Tradesperson					-0.011	(0.029)
Father Manual					0.028	(0.028)
Mother Manager/Professional					0.001	(0.030)
Mother Salesperson/Clerk					0.003	(0.021)
Mother Tradesperson					-0.010	(0.046)
Mother Manual					0.000	(0.024)
λ			-0.028	(0.019)	-0.040	(0.026)
Number of observations	1388		1388		1388	
P-value year dummies	0.000		0.000		0.000	
P-value regional dummies	0.001		0.001		0.001	
Log Likelihood	-214.88		-213.63		-207.64	
R^2	0.3591		0.3603		0.3658	

For women the OLS estimates of the returns to qualifications are slightly above those obtained for the whole sample. Once again these OLS estimates are significantly less that the IV estimates, which was also the case for the whole sample. The OLS estimates suggest a differential of around 70 per cent between an unqualified women and a women with a degree. The IV estimator, however, suggests that educational qualifications for women are endogenous and the corrected estimates are again significantly higher than the uncorrected estimates. The IV estimates are once again very close to those obtained for women in the previous Chapter.

From this section it is clear that the estimates of the returns to years of education for both men and women in our sibling sample using conventional cross-section estimation techniques, are broadly similar to those obtained in the previous Chapter for the entire male and female samples. The results that we have obtained here, therefore provide us with a benchmark to assess the importance of unobserved family attributes on estimates of the returns to education.

4.4.2 Simple Correlations Among the Sibling Variables

Table 4.9 shows the correlations among logarithmic wages, years of education, highest education qualification and experience as reported by each sibling. It shows that the correlation between siblings years of schooling is 0.41 and the correlation between siblings highest qualification is 0.44[2]. The correlation between log hourly earnings of the two siblings is 0.31. The correlations between sibling's education and wages are much smaller than those observed in Ashenfelter and Krueger's twins study where the correlation between years of education were 0.66 for identical twins and 0.54 for fraternal twins. The corresponding correlations between log hourly wages were 0.56 for identical twins and 0.36 for fraternal twins. It is also clear from the Table that our two measures of education are highly correlated for both older and younger siblings.

In Figure 4.1 we plot differences in sibling's log hourly earnings against

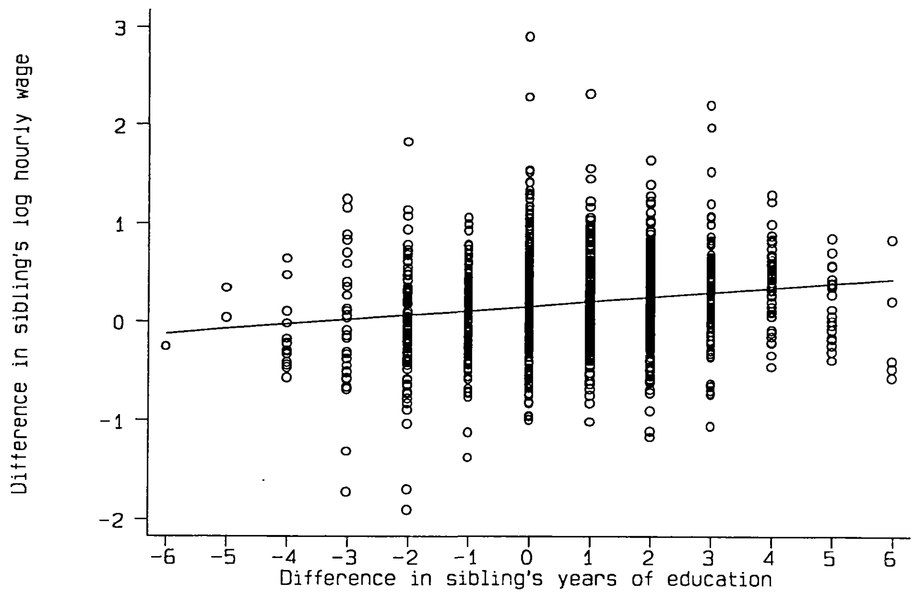
[2]This gives the correlation between the ordered highest qualification variable which ranges from zero (for those whose highest qualification is less than Year 10) to five (for those individual's with degrees).

differences in years of education. We see that differences in education between siblings are positively correlated with differences in log earnings between siblings. This will be picked up in our fixed effect models estimated below.

Table 4.9: Correlations among Sibling Variables

Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
(1) Years of Education-Elder	1.00							
(2) Years of Education-Younger	0.41	1.00						
(3) Highest Qualification-Elder	0.78	0.42	1.00					
(4) Highest Qualification -Younger	0.37	0.82	0.44	1.00				
(5) Experience-Elder	-0.41	0.09	-0.36	0.02	1.00			
(6) Experience-Younger	0.01	-0.22	-0.07	-0.24	0.60	1.00		
(7) Log Wage-Elder	0.33	0.25	0.23	0.20	0.19	0.22	1.00	
(8) Log Wage-Younger	0.22	0.37	0.13	0.25	0.37	0.43	0.31	1.00

Figure 4.1: Differences in Sibling's Wages and Years of Education



4.4.3 Within Family Returns to Education and Highest Qualifications

The results of the OLS, GLS and Fixed Effect estimates of the returns to years of education are given in Table 4.10. In the first column we present the simple OLS estimates of the returns to education. In column 2 we present the results of stacking equations (4.3) and (4.3) and estimating them by GLS. In the third column we present the results of stacking equations (4.6) and (4.7) and again undertaking GLS estimation. In these equations we include variables measuring sibling's education, experience and sex and the coefficients on these variables should measure the selection effects arising because of unobserved family attributes. We also included variables which vary by family, but not for individuals within a family such as parental education and occupation variables. The fourth column in this table presents the results of the fixed effect estimation procedure where unobserved family effects have been differenced out. In this final specification the explanatory variables are in difference form.

Table 4.10: Within Family Estimates of the Returns to Education

Variable	(i)-OLS		(ii)-GLS		(iii)-GLS		(iv)-Fixed Effect	
	Coef.	(S.E.)	Coef.	(S.E.)	Coef.	(S.E.)	Coef.	(S.E.)
Constant	0.086	(0.054)	0.089	(0.054)	-0.015	(0.063)	0.007	(0.022)
Years education	0.124	(0.004)	0.124	(0.004)	0.120	(0.004)	0.107	(0.011)
Experience	0.080	(0.003)	0.080	(0.003)	0.078	(0.003)	0.069	(0.008)
Male	0.044	(0.011)	0.043	(0.011)	0.045	(0.011)	0.033	(0.015)
Sibling's Years Education					0.011	(0.004)		
Sibling Experience					0.005	(0.003)		
Sibling Male					0.013	(0.011)		
Australian Born White	-0.022	(0.020)	-0.022	(0.019)	-0.024	(0.019)		
Australian Born Non-white	-0.037	(0.044)	-0.037	(0.060)	-0.031	(0.060)		
English Good (ESL)	-0.077	(0.025)	-0.077	(0.024)	-0.082	(0.024)		
English Poor (ESL)	-0.182	(0.059)	-0.182	(0.080)	-0.192	(0.080)		
Number of siblings	-0.002	(0.004)	-0.002	(0.004)	-0.003	(0.004)		
Mother Degree	0.079	(0.037)	0.080	(0.032)	0.077	(0.032)		
Mother Other Tertiary	0.049	(0.017)	0.049	(0.017)	0.047	(0.017)		
Father Degree	0.031	(0.021)	0.032	(0.021)	0.026	(0.021)		
Father Other Tertiary	-0.030	(0.024)	-0.030	(0.021)	-0.035	(0.021)		
Father Manager/Prof	-0.024	(0.019)	-0.023	(0.019)	-0.026	(0.019)		
Father Salesperson/Clerk	-0.027	(0.024)	-0.026	(0.024)	-0.026	(0.024)		
Father Tradesperson	0.010	(0.020)	0.010	(0.021)	0.009	(0.021)		
Father Manual	0.023	(0.019)	0.022	(0.020)	0.021	(0.020)		
Mother Manager/Prof	-0.045	(0.022)	-0.045	(0.018)	-0.048	(0.018)		
Mother Salesperson/Clerk	0.004	(0.014)	0.003	(0.014)	0.003	(0.014)		
Mother Tradesperson	0.031	(0.032)	0.030	(0.040)	0.032	(0.040)		
Mother Manual	0.010	(0.016)	0.010	(0.017)	0.010	(0.017)		
Number of observations	3352		3352		3352		1676	
P-value year dummies	0.000		0.000		0.000			
P-value regional dummies	0.000		0.000		0.000			
Log Likelihood	-731.65		-731.66		-726.43		-920.55	
R^2	0.3779		0.3779		0.3803		0.0724	

The OLS estimate of the return to education is 12.4 per cent. The GLS estimate in the second column is also 12.4 per cent. When we include variables measuring siblings educational outcomes the estimates suggest that unobserved family attributes result in a significant upward bias in the estimate of the return to education by around 1.1 percentage points and that the return is closer 10.9 per cent. The fixed effect estimation procedure also suggests an upward bias in the OLS estimate, and that the estimated return to education is around 10.7 per cent. Both of the within family estimation procedures also suggest that OLS significantly overestimates the returns to experience. No account has been taken here of possible measurement error problems and the biases resulting from correlation between siblings education level. In Table 4.9 we saw that the correlation between siblings years of education was 0.41. If there is no measurement error then our GLS and fixed effect estimates will be unaffected by this correlation. If however, there is even a small amount of measurement error, these estimates will underestimate the returns to education. For example, if we assume a reliability ratio of 0.95, then our fixed effect estimator will be biased down by around $0.05/(1-0.41) = 0.085$ or around 8.5 per cent as we from Chapter 2 in which case the OLS estimates would still be higher than our within family fixed effect estimator. We require a reliability ratio of around 90 per cent in order for our OLS and fixed effect estimates to be the same.

If we look at the returns to highest educational qualifications reported in Table (4.11) a similar story emerges. The OLS estimates presented in the first column again suggest significant returns to all educational qualifications. A person with a Degree receives on average a wage which is 72.1 per cent higher than individuals who left school before Year 10 and around 37 per cent higher than individuals who have only completed Year 12. The GLS estimates presented in the second column are almost identical to these OLS estimates. The estimates which specifically take into account biases due to unobserved family attributes, suggest once again that OLS estimates overstate the true returns to these educational qualifications, though the extent of the overestimation varies by qualification groups. The GLS estimation procedure in the third column suggests a return to a Degree of around $0.705 - 0.099$ or around 60 per cent which is around 12 percentage points less than the corresponding OLS estimate. The fixed effect estimate suggests a return to a degree of around 50 per cent which is again significantly less than the corresponding OLS estimate. Again in these tables, no account has been taken of possible biases resulting from measurement error, or correlations between unobserved individual effects and qualifications. Also in what we have done so far we have treated brothers, sisters and mixed sibling pairs as identical. We now go on to look at the reasonableness of this last assumption.

4.4.4 Sibling Types and the Returns to Education

We now split our sibling sample into pairs of brothers, sisters and mixed sibling pairs and look at whether the within family estimates to education vary by these sibling types. Tables (4.12), (4.12) and (4.12) show the correlation among brothers, sisters and mixed sibling pairs education, experience and wages. The first thing which is striking about these correlation matrices is how sister's educational outcomes are much more highly correlated than brothers and brother and sisters educational outcomes. The correlation between sister's years of education is 0.51 and their highest qualification 0.57. This compares with figures of 0.38 (years of education) and 0.38 (highest qualifications) for brothers and 0.38 (years of education) and 0.43 (highest qualifications) for brother and sister pairs. On, the other hand, the correlations between log wages is weakest for sisters and strongest for brother and sister pairs, though all are broadly similar.

We first concentrate on the within family estimates of the returns to education for brothers and these are presented in Table 4.15. The layout of this table is identical to those presented in the previous section. The

Table 4.11: Within Family Estimates of the Returns to Highest Qualifications

Variable	(i)-OLS		(ii)-GLS		(iii)-GLS		(iv)-Fixed Effect	
	Coef.	(S.E.)	Coef.	(S.E.)	Coef.	(S.E.)	Coef.	(S.E.)
Constant	1.226	(0.045)	1.231	(0.045)	1.137	(0.054)	0.048	(0.020)
Highest Qualification:								
Year 10	0.080	(0.033)	0.077	(0.032)	0.076	(0.032)	0.003	(0.047)
Year 11	0.176	(0.034)	0.171	(0.032)	0.165	(0.032)	0.037	(0.051)
Year 12	0.351	(0.033)	0.348	(0.032)	0.338	(0.033)	0.209	(0.055)
Year 12 & Tertiary	0.574	(0.036)	0.571	(0.035)	0.554	(0.036)	0.408	(0.067)
Degree	0.721	(0.039)	0.716	(0.038)	0.705	(0.039)	0.504	(0.079)
< Year 12 & Tertiary	0.282	(0.015)	0.280	(0.015)	0.272	(0.015)	0.201	(0.026)
Experience	0.078	(0.003)	0.077	(0.003)	0.075	(0.003)	0.053	(0.008)
Male	0.056	(0.011)	0.055	(0.011)	0.055	(0.011)	0.047	(0.015)
Sibling Highest Qual:								
Year 10					0.057	(0.032)		
Year 11					0.104	(0.032)		
Year 12					0.084	(0.033)		
Year 12 & Tertiary					0.066	(0.036)		
Degree					0.099	(0.039)		
< Year 12 & Tertiary					0.041	(0.015)		
Sibling Experience					0.006	(0.003)		
Sibling Male					0.007	(0.011)		
Australian Born White	-0.028	(0.020)	-0.028	(0.020)	-0.025	(0.020)		
Australian Born Non-white	-0.036	(0.045)	-0.035	(0.061)	-0.029	(0.061)		
English Good (ESL)	-0.073	(0.025)	-0.072	(0.025)	-0.075	(0.025)		
English Poor (ESL)	-0.181	(0.065)	-0.180	(0.081)	-0.198	(0.081)		
Number of siblings	-0.002	(0.004)	-0.002	(0.004)	-0.002	(0.004)		
Mother Degree	0.090	(0.037)	0.091	(0.033)	0.090	(0.033)		
Mother Other Tertiary	0.052	(0.017)	0.051	(0.017)	0.049	(0.017)		
Father Degree	0.041	(0.021)	0.041	(0.021)	0.044	(0.021)		
Father Other Tertiary	-0.023	(0.024)	-0.025	(0.021)	-0.023	(0.021)		
Father Manager/Prof	-0.023	(0.019)	-0.023	(0.020)	-0.022	(0.020)		
Father Salesperson/Clerk	-0.023	(0.024)	-0.022	(0.024)	-0.024	(0.024)		
Father Tradesperson	0.014	(0.020)	0.014	(0.021)	0.016	(0.021)		
Father Manual	0.032	(0.020)	0.033	(0.021)	0.031	(0.021)		
Mother Manager/Prof	-0.046	(0.022)	-0.046	(0.018)	-0.049	(0.018)		
Mother Salesperson/Clerk	0.001	(0.014)	0.000	(0.014)	0.001	(0.014)		
Mother Tradesperson	0.031	(0.033)	0.031	(0.041)	0.037	(0.040)		
Mother Manual	0.010	(0.016)	0.010	(0.018)	0.011	(0.018)		
Number of observations	3352		3352		3352		1676	
P-value year dummies	0.000		0.000		0.000			
P-value regional dummies	0.000		0.000		0.000			
Log Likelihood	-769.94		-770.00		-755.743		-920.54	
R^2	0.3635		0.3635		0.3689		0.0724	

Table 4.12: Correlations among Brother's Variables

Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
(1) Years of Education-Elder	1.00							
(2) Years of Education-Younger	0.38	1.00						
(3) Highest Qualification-Elder	0.71	0.37	1.00					
(4) Highest Qualification -Younger	0.28	0.76	0.38	1.00				
(5) Experience-Elder	-0.32	0.16	-0.27	0.13	1.00			
(6) Experience-Younger	0.03	-0.18	-0.02	-0.17	0.62	1.00		
(7) Log Wage-Elder	0.32	0.19	0.15	0.10	0.24	0.21	1.00	
(8) Log Wage-Younger	0.23	0.39	0.11	0.23	0.41	0.44	0.30	1.00

Table 4.13: Correlations among Sister's Variables

Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
(1) Years of Education-Elder	1.00							
(2) Years of Education-Younger	0.51	1.00						
(3) Highest Qualification-Elder	0.85	0.60	1.00					
(4) Highest Qualification -Younger	0.42	0.89	0.57	1.00				
(5) Experience-Elder	-0.46	-0.09	-0.43	-0.11	1.00			
(6) Experience-Younger	-0.05	-0.27	-0.16	-0.30	0.60	1.00		
(7) Log Wage-Elder	0.29	0.27	0.27	0.23	0.15	0.18	1.00	
(8) Log Wage-Younger	0.19	0.33	0.16	0.25	0.30	0.37	0.28	1.00

Table 4.14: Correlations among Mixed Sibling's Variables

Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
(1) Years of Education-Elder	1.00							
(2) Years of Education-Younger	0.38	1.00						
(3) Highest Qualification-Elder	0.79	0.37	1.00					
(4) Highest Qualification -Younger	0.40	0.82	0.43	1.00				
(5) Experience-Elder	-0.45	0.11	-0.40	0.00	1.00			
(6) Experience-Younger	0.02	-0.23	-0.07	-0.27	0.58	1.00		
(7) Log Wage-Elder	0.37	0.29	0.27	0.28	0.15	0.24	1.00	
(8) Log Wage-Younger	0.23	0.37	0.14	0.27	0.37	0.44	0.34	1.00

OLS estimate of the return to education for brothers is 12.5 per cent. The GLS estimate in the second column is also 12.5 per cent. The returns to experience are estimated in these two columns to be around 8.6 per cent. In the third columns, the coefficients on sibling's education and experience are insignificant and suggest a corrected estimate of the returns to education close to OLS estimates. Interestingly for men, our fixed effect estimate of the return to education is significantly above our OLS and GLS estimates which is contrary to the results obtained for the whole sample. This result is similar to that found by Ashenfelter and Krueger for their male twins. It provides some evidence that if we ignore unobserved family effects, we may underestimate the returns to years of education for men. This will certainly be true if we have a measurement error problem.

A very different story emerges for pairs of sisters. The OLS estimates of the returns to education are 10.3 per cent and the GLS estimate in the second column 10.1 per cent. When we include sister's education and experience there is no evidence of any significant selection effects. However, the fixed effect estimate of the return to education is well below the estimates

Table 4.15: Within-family Returns to Education for Brothers

Variable	(i)-OLS		(ii)-GLS		(iii)-GLS		(iv)-Fixed Effect	
	Coef.	(S.E.)	Coef.	(S.E.)	Coef.	(S.E.)	Coef.	(S.E.)
Constant	0.162	(0.098)	0.157	(0.094)	0.123	(0.109)	0.052	(0.036)
Years education	0.125	(0.007)	0.125	(0.007)	0.123	(0.007)	0.135	(0.019)
Experience	0.086	(0.004)	0.086	(0.004)	0.084	(0.005)	0.095	(0.015)
Sibling's Years Education					0.004	(0.007)		
Sibling Experience					0.005	(0.005)		
Australian Born White	0.002	(0.038)	0.003	(0.036)	0.000	(0.036)		
Australian Born Non-white	0.086	(0.067)	0.084	(0.092)	0.084	(0.092)		
English Good (ESL)	-0.089	(0.038)	-0.090	(0.039)	-0.093	(0.039)		
English Poor (ESL)	-0.168	(0.147)	-0.167	(0.155)	-0.175	(0.154)		
Number of siblings	-0.003	(0.007)	-0.004	(0.007)	-0.004	(0.007)		
Mother Degree	0.113	(0.082)	0.115	(0.064)	0.115	(0.065)		
Mother Other Tertiary	0.059	(0.027)	0.059	(0.028)	0.057	(0.028)		
Father Degree	0.041	(0.038)	0.040	(0.037)	0.041	(0.037)		
Father Other Tertiary	-0.062	(0.043)	-0.063	(0.034)	-0.063	(0.034)		
Father Manager/Prof	-0.068	(0.032)	-0.068	(0.036)	-0.068	(0.036)		
Father Salesperson/Clerk	-0.090	(0.039)	-0.087	(0.044)	-0.086	(0.044)		
Father Tradesperson	-0.015	(0.034)	-0.014	(0.040)	-0.014	(0.040)		
Father Manual	-0.031	(0.035)	-0.032	(0.039)	-0.032	(0.039)		
Mother Manager/Prof	-0.081	(0.038)	-0.080	(0.030)	-0.080	(0.030)		
Mother Salesperson/Clerk	0.039	(0.028)	0.039	(0.026)	0.038	(0.026)		
Mother Tradesperson	0.044	(0.075)	0.043	(0.083)	0.049	(0.083)		
Mother Manual	-0.006	(0.026)	-0.006	(0.030)	-0.008	(0.030)		
Number of observations	1196		1196		1196		598	
P-value year dummies	0.000		0.000		0.000			
P-value regional dummies	0.000		0.000		0.000			
Log Likelihood	-292.29		-292.32		-291.81		-348.66	
R^2	0.3926		0.3926		0.3931		0.1088	

obtained in the first three columns. The estimated return is now 6.8 per cent compared to our OLS estimate of 10.3 per cent. It should be remembered that sister's education outcomes are very highly correlated and if we assume an attenuation ratio of 0.9, our fixed effect estimate will be biased downwards by around 20 per cent.

Table 4.16: Within-family Returns to Education for Sisters

Variable	(i)-OLS		(ii)-GLS		(iii)-GLS		(iv)-Fixed Effect	
	Coef.	(S.E.)	Coef.	(S.E.)	Coef.	(S.E.)	Coef.	(S.E.)
Constant	0.238	(0.128)	0.246	(0.126)	0.258	(0.147)	0.098	(0.042)
Years education	0.103	(0.008)	0.101	(0.008)	0.101	(0.009)	0.068	(0.021)
Experience	0.070	(0.006)	0.069	(0.006)	0.070	(0.006)	0.041	(0.015)
Sibling's Years Education					0.000	(0.009)		
Sibling Experience					-0.004	(0.006)		
Australian Born White	0.009	(0.040)	0.023	(0.044)	0.024	(0.044)		
Australian Born Non-white	-0.235	(0.079)	-0.233	(0.156)	-0.235	(0.157)		
English Good (ESL)	0.035	(0.046)	0.037	(0.058)	0.040	(0.059)		
English Poor (ESL)	-0.092	(0.079)	-0.065	(0.114)	-0.058	(0.115)		
Number of siblings	0.007	(0.007)	0.007	(0.007)	0.008	(0.007)		
Mother Degree	0.007	(0.073)	0.005	(0.069)	0.007	(0.069)		
Mother Other Tertiary	0.067	(0.043)	0.079	(0.045)	0.080	(0.045)		
Father Degree	-0.013	(0.044)	-0.014	(0.047)	-0.015	(0.048)		
Father Other Tertiary	-0.003	(0.050)	0.002	(0.046)	0.003	(0.047)		
Father Manager/Prof	0.008	(0.048)	0.011	(0.043)	0.011	(0.043)		
Father Salesperson/Clerk	0.061	(0.073)	0.065	(0.058)	0.063	(0.058)		
Father Tradesperson	0.045	(0.048)	0.052	(0.046)	0.052	(0.046)		
Father Manual	0.055	(0.047)	0.059	(0.048)	0.058	(0.048)		
Mother Manager/Prof	0.051	(0.041)	0.061	(0.043)	0.061	(0.043)		
Mother Salesperson/Clerk	0.064	(0.030)	0.071	(0.030)	0.073	(0.030)		
Mother Tradesperson	-0.033	(0.065)	-0.012	(0.083)	-0.015	(0.083)		
Mother Manual	-0.023	(0.042)	-0.014	(0.043)	-0.014	(0.043)		
Number of observations	620		620		620		310	
P-value year dummies	0.000		0.000		0.000			
P-value regional dummies	0.000		0.000		0.000			
Log Likelihood	-99.64		-100.05		-99.94		-157.54	
R^2	0.3595		0.3586		0.3589		0.0372	

In Table 4.17 we present the results for the brother and sister pairings in our sibling sample. These results for both brother and sister pairs suggest that the within family estimates of the returns to education are lower than our conventional OLS estimate. Our OLS estimate of the return to education for this sample is 12.9 per cent. From the third column we see evidence of a significant selection term on sibling's years of education which suggests that the return to education is closer to 10.6 per cent. The fixed effect estimate also tells a similar story suggesting a return of around 10.1 per cent. There also appears to be upward bias in the OLS estimate of the return to experience in this sample.

Table 4.17: Within-family Returns to Education for Mixed Sibling Pairs

Variable	(i)-OLS		(ii)-GLS		(iii)-GLS		(iv)-Fixed Effect	
	Coef.	(S.E.)	Coef.	(S.E.)	Coef.	(S.E.)	Coef.	(S.E.)
Constant	0.034	(0.078)	0.033	(0.078)	-0.125	(0.091)	0.014	(0.034)
Years education	0.129	(0.006)	0.129	(0.005)	0.124	(0.006)	0.101	(0.168)
Experience	0.079	(0.004)	0.079	(0.004)	0.076	(0.004)	0.062	(0.015)
Sibling's Years Education					0.018	(0.005)		
Sibling Experience					0.008	(0.004)		
Male	0.033	(0.015)	0.033	(0.015)	0.034	(0.015)	0.034	(0.015)
Australian Born White	-0.030	(0.032)	-0.030	(0.029)	-0.027	(0.029)		
Australian Born Non-white	-0.123	(0.060)	-0.124	(0.095)	-0.106	(0.095)		
English Good (ESL)	-0.104	(0.043)	-0.106	(0.038)	-0.111	(0.038)		
English Poor (ESL)	-0.088	(0.147)	-0.088	(0.171)	-0.095	(0.170)		
Number of siblings	-0.009	(0.007)	-0.009	(0.006)	-0.010	(0.006)		
Mother Degree	0.096	(0.051)	0.100	(0.044)	0.096	(0.044)		
Mother Other Tertiary	0.027	(0.026)	0.026	(0.026)	0.032	(0.026)		
Father Degree	0.031	(0.032)	0.031	(0.029)	0.019	(0.029)		
Father Other Tertiary	0.013	(0.035)	0.014	(0.033)	0.005	(0.033)		
Father Manager/Prof	-0.011	(0.026)	-0.009	(0.027)	-0.015	(0.027)		
Father Salesperson/Clerk	-0.025	(0.033)	-0.023	(0.034)	-0.022	(0.034)		
Father Tradesperson	-0.005	(0.029)	-0.005	(0.029)	-0.004	(0.030)		
Father Manual	0.042	(0.026)	0.042	(0.028)	0.038	(0.028)		
Mother Manager/Prof	-0.038	(0.033)	-0.039	(0.027)	-0.044	(0.027)		
Mother Salesperson/Clerk	-0.033	(0.019)	-0.033	(0.020)	-0.032	(0.020)		
Mother Tradesperson	0.050	(0.045)	0.049	(0.056)	0.043	(0.055)		
Mother Manual	0.039	(0.023)	0.040	(0.025)	0.041	(0.025)		
Number of observations	1536		768		768		768	
P-value year dummies	0.000		0.000		0.000			
P-value regional dummies	0.000		0.000		0.000			
Log Likelihood	-295.55		-295.59		-290.00		-408.22	
R^2	0.4042		0.4042		0.4085		0.0634	

In Table 4.18 we present estimates of the within family returns to highest qualifications for brothers. All four columns of the table give remarkably similar estimates of the returns to qualifications for brothers. If measurement error is a problem, then our fixed effect estimates suggest that OLS may underestimate the returns to qualifications. This is impossible to gauge without appropriate instruments for qualifications.

For sisters, there is once again conflicting evidence about the importance of unobserved family attributes in estimating returns to qualifications. The first three columns of the table give remarkably similar results and none of the selection terms in the third column are significant. However, the fixed

Table 4.18: Within Family Returns to Highest Qualifications for Brothers

Variable	(i)-OLS		(ii)-GLS		(iii)-GLS		(iv)-Fixed Effect	
	Coef.	(S.E.)	Coef.	(S.E.)	Coef.	(S.E.)	Coef.	(S.E.)
Constant	1.348	(0.076)	1.349	(0.081)	1.308	(0.099)	0.005	(0.031)
Highest Qualification:								
Year 10	0.016	(0.052)	0.016	(0.057)	-0.004	(0.058)	-0.034	(0.081)
Year 11	0.102	(0.052)	0.102	(0.058)	0.082	(0.059)	0.015	(0.088)
Year 12	0.271	(0.053)	0.271	(0.059)	0.255	(0.060)	0.225	(0.095)
Year 12 & Tertiary	0.542	(0.058)	0.541	(0.066)	0.524	(0.068)	0.474	(0.122)
Degree	0.616	(0.065)	0.618	(0.072)	0.611	(0.075)	0.644	(0.158)
< Year 12 & Tertiary	0.324	(0.025)	0.323	(0.025)	0.324	(0.025)	0.252	(0.038)
Experience	0.083	(0.004)	0.083	(0.004)	0.082	(0.005)	0.070	(0.014)
Sibling Highest Qual:								
Year 10					0.009	(0.058)		
Year 11					0.056	(0.059)		
Year 12					0.019	(0.059)		
Year 12 & Tertiary					0.032	(0.067)		
Degree					-0.069	(0.074)		
< Year 12 & Tertiary					0.066	(0.025)		
Sibling Experience					0.008	(0.005)		
Australian Born White	0.026	(0.037)	0.026	(0.036)	0.029	(0.036)		
Australian Born Non-white	0.111	(0.069)	0.111	(0.092)	0.110	(0.092)		
English Good (ESL)	-0.078	(0.040)	-0.077	(0.039)	-0.078	(0.039)		
English Poor (ESL)	-0.194	(0.140)	-0.193	(0.158)	-0.202	(0.155)		
Number of siblings	-0.001	(0.007)	-0.002	(0.007)	-0.004	(0.007)		
Mother Degree	0.149	(0.086)	0.148	(0.065)	0.158	(0.066)		
Mother Other Tertiary	0.067	(0.028)	0.067	(0.028)	0.065	(0.028)		
Father Degree	0.057	(0.038)	0.057	(0.038)	0.075	(0.038)		
Father Other Tertiary	-0.057	(0.044)	-0.057	(0.035)	-0.058	(0.035)		
Father Manager/Prof	-0.062	(0.032)	-0.062	(0.037)	-0.062	(0.037)		
Father Salesperson/Clerk	-0.092	(0.039)	-0.091	(0.044)	-0.099	(0.044)		
Father Tradesperson	-0.001	(0.034)	-0.001	(0.041)	0.000	(0.040)		
Father Manual	-0.008	(0.035)	-0.008	(0.039)	-0.012	(0.039)		
Mother Manager/Prof	-0.089	(0.038)	-0.089	(0.030)	-0.082	(0.031)		
Mother Salesperson/Clerk	0.034	(0.029)	0.033	(0.027)	0.027	(0.027)		
Mother Tradesperson	0.055	(0.077)	0.057	(0.084)	0.076	(0.084)		
Mother Manual	0.000	(0.026)	0.000	(0.031)	-0.011	(0.031)		
Number of observations	1196		1196		1196		598	
P-value year dummies	0.000		0.000		0.000			
P-value regional dummies	0.000		0.000		0.000			
Log Likelihood	-300.19		-300.19		-289.69		-346.47	
R^2	0.3846		0.3846		0.3953		0.1154	

effect estimates of the returns to qualifications are significantly below the OLS estimates. This may in part be due to measurement error problems, but this is unlikely that this is the whole story. We saw in the previous Chapter that it was important to control for unobserved correlated individual effects in estimating the returns to schooling and education for women. The estimation procedures we are using in this Chapter will not correct for correlated individual effects which are not specifically related to the family. In order to correct for such biases we again need to rely on instrumental variable techniques. Unfortunately in our data, there appears to be no obvious instruments that we can use when using within family estimation procedures.

The within family estimates for brother and sister pairs once again clearly suggest that OLS estimates overstate the returns to qualifications by not taking into account correlated family effects. The OLS estimate of the return to a degree is around 80 per cent whereas the results in column 3 suggest a return of around 50 per cent and the fixed effect estimator a return of around 47 per cent. Unlike for sisters, our proxy and fixed effect estimation procedures give remarkable similar results.

4.4.5 Do family attributes affect sibling's wages in an identical manner?

As mentioned in the introduction and methodology sections, one of the crucial assumptions of the models considered in this Chapter is that unobserved family attributes affect the wages of older and younger siblings in an identical manner. In this section we look at how valid this assumption is, by looking at whether observed family attributes, such as parents education and occupation as well as the number of siblings obey this assumption (which is also assumed in these models). If they do, and we enter them as levels in our fixed effect model, the coefficients should be insignificant. We have done this for our highest education specification for the whole sample, as well as brothers, sisters and mixed sibling pairs in Table ??. The results from this Table

Table 4.19: Within Family Returns to Highest Qualifications for Sisters

Variable	(i)-OLS		(ii)-GLS		(iii)-GLS		(iv)-Fixed Effect	
	Coef.	(S.E.)	Coef.	(S.E.)	Coef.	(S.E.)	Coef.	(S.E.)
Constant	1.221	(0.089)	1.204	(0.102)	1.175	(0.129)	0.121	(0.040)
Highest Qualification:								
Year 10	0.028	(0.044)	0.032	(0.070)	0.033	(0.071)	0.019	(0.072)
Year 11	0.159	(0.052)	0.149	(0.073)	0.143	(0.074)	0.061	(0.084)
Year 12	0.246	(0.051)	0.240	(0.074)	0.238	(0.076)	0.107	(0.103)
Year 12 & Tertiary	0.451	(0.056)	0.445	(0.076)	0.440	(0.080)	0.300	(0.114)
Degree	0.609	(0.065)	0.606	(0.084)	0.613	(0.087)	0.349	(0.122)
< Year 12 & Tertiary	0.187	(0.035)	0.189	(0.036)	0.188	(0.038)	0.090	(0.065)
Experience	0.070	(0.006)	0.067	(0.006)	0.070	(0.006)	0.034	(0.014)
Sibling Highest Qual:								
Year 10					0.006	(0.071)		
Year 11					0.062	(0.074)		
Year 12					0.048	(0.076)		
Year 12 & Tertiary					-0.019	(0.080)		
Degree					0.033	(0.089)		
< Year 12 & Tertiary					0.021	(0.038)		
Sibling Experience					-0.004	(0.006)		
Australian Born White	0.001	(0.039)	0.017	(0.044)	0.027	(0.045)		
Australian Born Non-white	-0.230	(0.089)	-0.237	(0.158)	-0.221	(0.158)		
English Good (ESL)	0.022	(0.047)	0.022	(0.059)	0.019	(0.060)		
English Poor (ESL)	-0.089	(0.098)	-0.043	(0.116)	-0.046	(0.118)		
Number of siblings	0.009	(0.007)	0.009	(0.008)	0.009	(0.008)		
Mother Degree	0.018	(0.070)	0.019	(0.070)	0.027	(0.070)		
Mother Other Tertiary	0.061	(0.042)	0.075	(0.045)	0.063	(0.046)		
Father Degree	0.010	(0.044)	0.004	(0.048)	0.016	(0.049)		
Father Other Tertiary	-0.008	(0.053)	-0.008	(0.047)	-0.005	(0.049)		
Father Manager/Prof	0.011	(0.047)	0.017	(0.044)	0.018	(0.044)		
Father Salesperson/Clerk	0.063	(0.072)	0.069	(0.059)	0.062	(0.059)		
Father Tradesperson	0.044	(0.048)	0.053	(0.047)	0.054	(0.047)		
Father Manual	0.046	(0.049)	0.053	(0.049)	0.055	(0.049)		
Mother Manager/Prof	0.065	(0.040)	0.082	(0.044)	0.070	(0.044)		
Mother Salesperson/Clerk	0.067	(0.034)	0.079	(0.031)	0.081	(0.032)		
Mother Tradesperson	-0.044	(0.068)	-0.014	(0.084)	-0.023	(0.085)		
Mother Manual	-0.030	(0.043)	-0.021	(0.043)	-0.011	(0.044)		
Number of observations	620		620		620		310	
P-value year dummies	0.000		0.000		0.000			
P-value regional dummies	0.000		0.000		0.000			
Log Likelihood	-103.08		-103.81		-100.33		-156.79	
R^2	0.3523		0.3508		0.3581		0.0714	

Table 4.20: Within Family Returns to Highest Qualifications for Mixed Sibling Pairs

Variable	(i)-OLS		(ii)-GLS		(iii)-GLS		(iv)-Fixed Effect	
	Coef.	(S.E.)	Coef.	(S.E.)	Coef.	(S.E.)	Coef.	(S.E.)
Constant	1.198	(0.068)	1.200	(0.063)	1.093	(0.075)	0.056	(0.033)
Highest Qualification:								
Year 10	0.138	(0.055)	0.136	(0.045)	0.132	(0.045)	0.036	(0.078)
Year 11	0.211	(0.058)	0.208	(0.046)	0.199	(0.047)	0.048	(0.083)
Year 12	0.427	(0.055)	0.424	(0.046)	0.403	(0.046)	0.235	(0.091)
Year 12 & Tertiary	0.640	(0.060)	0.638	(0.049)	0.601	(0.050)	0.389	(0.109)
Degree	0.799	(0.065)	0.794	(0.054)	0.771	(0.056)	0.468	(0.124)
< Year 12 & Tertiary	0.275	(0.023)	0.273	(0.022)	0.260	(0.022)	0.187	(0.044)
Experience	0.076	(0.004)	0.076	(0.004)	0.072	(0.004)	0.044	(0.014)
Sibling Highest Qual:								
Year 10					0.072	(0.045)		
Year 11					0.112	(0.046)		
Year 12					0.100	(0.046)		
Year 12 & Tertiary					0.103	(0.050)		
Degree					0.180	(0.056)		
< Year 12 & Tertiary					0.035	(0.022)		
Sibling Experience					0.009	(0.004)		
Male	0.048	(0.015)	0.048	(0.015)	0.050	(0.016)	0.047	(0.016)
Australian Born White	-0.046	(0.032)	-0.047	(0.030)	-0.040	(0.030)		
Australian Born Non-white	-0.097	(0.061)	-0.097	(0.098)	-0.093	(0.098)		
English Good (ESL)	-0.104	(0.044)	-0.106	(0.039)	-0.110	(0.039)		
English Poor (ESL)	-0.127	(0.154)	-0.130	(0.176)	-0.147	(0.176)		
Number of siblings	-0.009	(0.007)	-0.009	(0.006)	-0.011	(0.006)		
Mother Degree	0.101	(0.048)	0.103	(0.045)	0.101	(0.044)		
Mother Other Tertiary	0.033	(0.027)	0.033	(0.026)	0.043	(0.026)		
Father Degree	0.034	(0.031)	0.034	(0.030)	0.025	(0.030)		
Father Other Tertiary	0.024	(0.033)	0.024	(0.033)	0.016	(0.033)		
Father Manager/Prof	-0.022	(0.027)	-0.020	(0.028)	-0.019	(0.028)		
Father Salesperson/Clerk	-0.020	(0.033)	-0.018	(0.034)	-0.018	(0.034)		
Father Tradesperson	-0.007	(0.030)	-0.007	(0.030)	-0.002	(0.030)		
Father Manual	0.048	(0.027)	0.048	(0.028)	0.046	(0.028)		
Mother Manager/Prof	-0.048	(0.033)	-0.049	(0.027)	-0.056	(0.027)		
Mother Salesperson/Clerk	-0.044	(0.019)	-0.043	(0.020)	-0.042	(0.020)		
Mother Tradesperson	0.040	(0.048)	0.038	(0.057)	0.040	(0.057)		
Mother Manual	0.037	(0.023)	0.038	(0.026)	0.040	(0.026)		
Number of observations	1536		1536		1536		768	
P-value year dummies	0.000		0.000		0.000			
P-value regional dummies	0.000		0.000		0.000			
Log Likelihood	-311.46		-311.48		-303.12		-408.80	
R^2	0.3917		0.3917		0.3983		0.0620	

cast doubt on the validity of this assumption, with family variables jointly significant in all but the sisters model. This is clearly something which needs to be examined in more detail in future work using within family fixed effect estimation techniques.

Table 4.21: Fixed Effect Estimates and Observed Family Characteristics

Variable	Whole Sample		Brothers		Sisters		Mixed	
	Coef.	(S.E.)	Coef.	(S.E.)	Coef.	(S.E.)	Coef.	(S.E.)
Constant	0.026	(0.045)	-0.013	(0.085)	0.053	(0.102)	0.023	(0.064)
Highest Qualification:								
Year 10	0.003	(0.046)	-0.048	(0.084)	0.037	(0.076)	0.001	(0.076)
Year 11	0.035	(0.050)	-0.008	(0.091)	0.080	(0.088)	0.021	(0.082)
Year 12	0.211	(0.055)	0.196	(0.097)	0.137	(0.109)	0.198	(0.092)
Year 12 & Tertiary	0.418	(0.066)	0.448	(0.121)	0.337	(0.126)	0.352	(0.111)
Degree	0.522	(0.079)	0.605	(0.168)	0.393	(0.136)	0.446	(0.124)
< Year 12 & Tertiary	0.200	(0.026)	0.255	(0.038)	0.088	(0.071)	0.169	(0.045)
Experience	0.054	(0.008)	0.066	(0.014)	0.037	(0.018)	0.042	(0.014)
Number of siblings	0.052	(0.015)	0.026	(0.012)	-0.005	(0.014)	0.051	(0.016)
Male	0.009	(0.008)					0.010	(0.014)
Mother Degree	0.014	(0.076)	-0.051	(0.134)	0.118	(0.170)	-0.026	(0.102)
Mother Other Tertiary	-0.007	(0.033)	-0.051	(0.055)	-0.037	(0.068)	0.063	(0.049)
Father Degree	0.008	(0.040)	0.055	(0.073)	-0.009	(0.074)	-0.025	(0.064)
Father Other Tertiary	-0.097	(0.047)	-0.069	(0.093)	-0.098	(0.074)	-0.158	(0.067)
Father Manager/Prof	-0.028	(0.038)	-0.075	(0.065)	0.034	(0.096)	-0.008	(0.053)
Father Salesperson/Clerk	-0.051	(0.045)	-0.115	(0.077)	0.051	(0.140)	0.019	(0.061)
Father Tradesperson	0.011	(0.040)	0.011	(0.068)	0.027	(0.097)	0.024	(0.057)
Father Manual	0.088	(0.039)	0.054	(0.069)	0.032	(0.105)	0.133	(0.053)
Mother Manager/Prof	0.001	(0.044)	-0.063	(0.073)	0.143	(0.087)	0.009	(0.072)
Mother Salesperson/Clerk	-0.018	(0.030)	-0.043	(0.068)	0.107	(0.063)	-0.053	(0.037)
Mother Tradesperson	0.201	(0.059)	0.403	(0.098)	0.166	(0.133)	0.025	(0.067)
Mother Manual	-0.006	(0.030)	0.025	(0.049)	0.095	(0.085)	-0.044	(0.042)
Number of observations	1676		598		310		768	
P-value family variables	0.000		0.000		0.6371		0.011	
Log Likelihood	-899.94		-329.99		-151.61		-395.88	
R^2	0.0949		0.1656		0.0734		0.0931	

4.5 Conclusions

In this Chapter we have utilised a sibling sub-sample of the ALS and AYS data used in the previous Chapter. The characteristics of this sample are similar to the main sample used in the previous Chapter except that men are over-represented. We have used this sibling sample to estimate within family returns to education and highest qualification. We use two methods. The first involves proxying the family effect using information from both siblings. The second uses fixed effect methods and looks at how differences in the education of siblings explains differences in earnings between the two siblings. If there is a common family effect which is correlated with education, this will be eliminated using such a procedure.

There is some evidence for the whole sample, and for sisters and mixed sibling pairs, that OLS estimates of the returns to schooling may be biased upward because of the omission of family background variables. This result is strongest for mixed sibling pairs and only true for women when we used fixed effect estimation. For brothers there is some weak evidence that OLS estimates may be biased downward. We have not made any adjustments for measurement error in estimating these returns which means that all our estimates may be downward biased. Our results also cast doubts as to whether there is a common family effect which affects siblings in an identical manner. This throws into question the validity of the models used in this Chapter for estimating the returns to education for our particular sibling sample.

These concerns aside, our results for men are broadly in line with those found by Ashenfelter and Krueger [11]. In terms of Card's model, within family estimates will be above OLS estimates if relative variation in discount rates (which reflects differences in access to funds and tastes for education) is reduced within families compared to the population and schooling is more highly correlated with ability within families than across the population. If the opposite is true, then within family estimates will be below OLS estimates and this appears to be the case with mixed sibling pairs (ignoring measurement error bias) and possibly sisters. This suggests that the sex composition of families may be important in determining the returns to education and qualifications. We will look at this issue again in Chapter5.

Appendices

A.4.1 The Age Distribution of the AYS and ALS sibling sample

Table 4.22: Age Distribution of the ALS and AYS Sibling Sample

				Year				
Age Group	1985	1986	1987	1988	1989	1990	1991	TOTAL
16 year olds	29	0	0	0	28	15	3	75
	(38.67)	(0.00)	(0.00)	(0.00)	(37.33)	(20.00)	(4.00)	(100.00)
	[4.85]	[0.00]	[0.00]	[0.00]	[8.05]	[3.57]	[0.86]	[2.24]
17 year olds	47	66	0	0	31	51	21	216
	(21.76)	(30.56)	(0.00)	(0.00)	(14.35)	(23.61)	(9.72)	(100.00)
	[7.86]	[10.96]	[0.00]	[0.00]	[8.91]	[12.14]	[6.03]	[6.44]
18 year olds	88	60	77	0	35	52	47	359
	(24.51)	(16.71)	(21.45)	(0.00)	(9.75)	(14.48)	(13.09)	(100.00)
	[14.72]	[9.97]	[13.32]	[0.00]	[10.06]	[12.38]	[13.51]	[10.71]
19 year olds	85	101	61	71	35	44	40	437
	(19.45)	(23.11)	(13.96)	(16.25)	(8.01)	(10.07)	(9.15)	(100.00)
	[14.21]	[16.78]	[10.55]	[15.50]	[10.06]	[10.48]	[11.49]	[13.04]
20 year olds	84	88	100	60	28	34	38	432
	(19.44)	(20.37)	(23.15)	(13.89)	(6.48)	(7.87)	(8.80)	(100.00)
	[14.05]	[14.62]	[17.30]	[13.10]	[8.05]	[8.10]	[10.92]	[12.89]
21 year olds	74	89	92	90	37	40	21	443
	(16.70)	(20.09)	(20.77)	(20.32)	(8.35)	(9.03)	(4.74)	(100.00)
	[12.37]	[14.78]	[15.92]	[19.65]	[10.63]	[9.52]	[6.03]	[13.22]
22 year olds	74	67	81	81	56	44	39	442
	(16.74)	(15.16)	(18.33)	(18.33)	(12.67)	(9.95)	(8.82)	(100.00)
	[12.37]	[11.13]	[14.01]	[17.69]	[16.09]	[10.48]	[11.21]	[13.19]
23 year olds	61	63	64	60	47	52	39	386
	(15.80)	(16.32)	(16.58)	(15.54)	(12.18)	(13.47)	(10.10)	(100.00.00)
	[10.20]	[10.47]	[11.07]	[13.10]	[13.51]	[12.38]	[11.21]	[11.52]
24 year olds	33	48	59	49	22	49	44	304
	(10.86)	(15.79)	(19.41)	(16.12)	(7.24)	(16.12)	(14.47)	(100.00)
	[5.52]	[7.97]	[10.21]	[10.70]	[6.32]	[11.67]	[12.64]	[9.07]
25 year olds	23	20	44	47	29	39	56	258
	(8.91)	(7.75)	(17.05)	(18.22)	(11.24)	(15.12)	(21.71)	(100.00)
	[3.85]	[3.32]	[7.61]	[10.26]	[8.33]	[9.29]	[16.09]	[7.70]
All Persons	602	602	580	458	348	422	348	3352
	(17.84)	(17.96)	(17.24)	(13.66)	(10.38)	(12.53)	(10.38)	(100.00)
	[100.00]	[100.00]	[100.00]	[100.00]	[100.00]	[100.00]	[100.00]	[100.00]

Note: Figures in parentheses give the age distribution (per cent) across years and figures in square brackets give the age distribution [per cent] within each year.

A.4.2 Summary Statistics

Table 4.23: Summary Statistics

Variable	Males		Females		Persons	
	1964 Observations		1388 Observations		3352 Observations	
	Mean	(Std Dev.)	Mean	(Std Dev.)	Mean	(Std Dev.)
Log real hourly wage	1.816	(0.400)	1.783	(0.353)	1.802	(0.382)
Real hourly wage	6.642	(2.714)	6.332	(2.557)	6.514	(2.654)
Age	20.852	(2.451)	20.875	(2.362)	20.862	(2.414)
Australian Born White	0.893	(0.310)	0.888	(0.315)	0.891	(0.312)
Australian Born Non-white	0.010	(0.098)	0.007	(0.085)	0.009	(0.093)
Mother Born Australia	0.720	(0.449)	0.754	(0.431)	0.734	(0.442)
Father Born Australia	0.694	(0.461)	0.711	(0.453)	0.701	(0.458)
English Good (ESL)	0.065	(0.247)	0.055	(0.229)	0.061	(0.240)
English Poor (ESL)	0.003	(0.055)	0.006	(0.080)	0.004	(0.067)
Other City at 14	0.177	(0.381)	0.178	(0.383)	0.177	(0.382)
Country Town at 14	0.188	(0.391)	0.215	(0.411)	0.199	(0.400)
Rural Area at 14	0.080	(0.272)	0.057	(0.232)	0.071	(0.256)
Overseas at 14	0.009	(0.093)	0.011	(0.103)	0.010	(0.097)
Lived with mother only at 14	0.052	(0.222)	0.065	(0.246)	0.057	(0.232)
Lived with father only at 14	0.004	(0.064)	0.015	(0.122)	0.009	(0.093)
Lived with neither parent at 14	0.003	(0.050)	0.003	(0.054)	0.003	(0.052)
Mother Degree	0.028	(0.165)	0.037	(0.188)	0.032	(0.175)
Mother Other Tertiary	0.135	(0.342)	0.103	(0.304)	0.122	(0.327)
Father Degree	0.087	(0.282)	0.097	(0.296)	0.091	(0.288)
Father Other Tertiary	0.076	(0.265)	0.076	(0.265)	0.076	(0.265)
Father Manager/Professional	0.392	(0.488)	0.384	(0.487)	0.389	(0.488)
Father Salesperson/Clerk	0.107	(0.309)	0.086	(0.281)	0.098	(0.298)
Father Tradesperson	0.189	(0.392)	0.197	(0.398)	0.192	(0.394)
Father Manual	0.212	(0.409)	0.223	(0.417)	0.217	(0.412)
Mother Manager/Professional	0.123	(0.329)	0.128	(0.334)	0.125	(0.331)
Mother Salesperson/Clerk	0.193	(0.395)	0.227	(0.419)	0.207	(0.405)
Mother Tradesperson	0.018	(0.134)	0.019	(0.138)	0.019	(0.136)
Mother Manual	0.123	(0.328)	0.128	(0.334)	0.125	(0.330)
Number of siblings	2.584	(1.396)	2.605	(1.493)	2.592	(1.437)
Number of older siblings	1.210	(1.284)	1.333	(1.378)	1.261	(1.325)
School Victoria	0.251	(0.433)	0.279	(0.449)	0.262	(0.440)
School Queensland	0.137	(0.344)	0.136	(0.343)	0.137	(0.344)
School South Australia	0.061	(0.240)	0.080	(0.271)	0.069	(0.253)
School Western Australia	0.084	(0.277)	0.085	(0.279)	0.084	(0.278)
School Tasmania	0.021	(0.143)	0.042	(0.200)	0.030	(0.169)
School Northern Territory	0.006	(0.075)	0.015	(0.122)	0.010	(0.097)
School ACT	0.019	(0.138)	0.001	(0.027)	0.012	(0.107)
Catholic School	0.210	(0.408)	0.197	(0.398)	0.205	(0.404)
Private School	0.057	(0.232)	0.058	(0.233)	0.057	(0.232)
Experience	4.092	(2.206)	3.922	(2.279)	4.022	(2.238)
Years of Education	11.760	(1.536)	11.954	(1.615)	11.840	(1.572)
Highest Qualification:						
Degree	0.055	(0.228)	0.063	(0.242)	0.058	(0.234)
Year 12 & Tertiary	0.075	(0.263)	0.161	(0.367)	0.110	(0.313)
Year 12	0.242	(0.428)	0.267	(0.443)	0.252	(0.434)
Year 11	0.231	(0.421)	0.216	(0.412)	0.225	(0.417)
Year 10	0.367	(0.482)	0.261	(0.439)	0.323	(0.468)
$<$ Year 10	0.031	(0.174)	0.032	(0.177)	0.032	(0.175)
$<$ Year 12 & Tertiary	0.232	(0.422)	0.168	(0.374)	0.206	(0.404)
Male					0.586	(0.493)

A.4.3 The Determinants of Education Outcomes

Table 4.24: The Determinants of Education Outcomes

Variable	Years of Full-time Education				Highest Qualification	
	Coef.	(S.E.)	Coef.	(S.E.)	Coef.	(S.E.)
Constant	12.083	(0.334)				
Australian Born White	0.352	(0.103)	0.260	(0.077)	0.273	(0.078)
Australian Born Non-white	-0.163	(0.282)	-0.091	(0.212)	0.070	(0.215)
Mother Born Australia	-0.019	(0.086)	-0.016	(0.064)	-0.024	(0.065)
Father Born Australia	-0.270	(0.078)	-0.180	(0.058)	-0.239	(0.059)
English Good (ESL)	-0.019	(0.118)	-0.009	(0.088)	0.045	(0.090)
English Poor (ESL)	-0.042	(0.373)	-0.039	(0.281)	-0.295	(0.286)
Other City at 14	-0.003	(0.071)	-0.002	(0.053)	-0.091	(0.054)
Country Town at 14	-0.372	(0.069)	-0.274	(0.052)	-0.333	(0.053)
Rural Area at 14	-0.021	(0.104)	-0.011	(0.078)	-0.116	(0.079)
Overseas at 14	0.033	(0.264)	0.005	(0.198)	-0.541	(0.205)
Lived with mother only at 14	0.035	(0.156)	-0.052	(0.118)	-0.178	(0.120)
Lived with father only at 14	0.671	(0.268)	0.481	(0.200)	0.518	(0.206)
Lived with neither parent at 14	-0.213	(0.480)	-0.137	(0.364)	0.130	(0.364)
Mother Degree	0.601	(0.148)	0.442	(0.111)	0.459	(0.113)
Mother Other Tertiary	0.116	(0.079)	0.096	(0.060)	0.140	(0.061)
Father Degree	0.666	(0.094)	0.450	(0.071)	0.535	(0.072)
Father Other Tertiary	0.501	(0.097)	0.363	(0.073)	0.350	(0.074)
Father Manager/Professional	0.404	(0.126)	0.286	(0.095)	0.215	(0.096)
Father Salesperson/Clerk	0.323	(0.142)	0.215	(0.107)	0.184	(0.109)
Father Tradesperson	0.477	(0.131)	0.337	(0.099)	0.269	(0.100)
Father Manual	0.283	(0.129)	0.187	(0.097)	0.032	(0.099)
Mother Manager/Professional	0.213	(0.083)	0.169	(0.062)	0.176	(0.063)
Mother Salesperson/Clerk	0.034	(0.065)	0.051	(0.049)	0.048	(0.050)
Mother Tradesperson	-0.014	(0.184)	0.022	(0.138)	0.074	(0.139)
Mother Manual	-0.086	(0.080)	-0.077	(0.060)	-0.084	(0.061)
Number of siblings	-0.039	(0.025)	-0.029	(0.019)	-0.033	(0.019)
Number of older siblings	-0.088	(0.027)	-0.062	(0.020)	-0.063	(0.021)
School Victoria	-0.014	(0.064)	0.028	(0.048)	0.187	(0.049)
School Queensland	0.471	(0.078)	0.382	(0.059)	0.473	(0.060)
School South Australia	0.451	(0.104)	0.394	(0.078)	0.596	(0.078)
School Western Australia	0.161	(0.096)	0.159	(0.072)	-0.009	(0.074)
School Tasmania	-0.924	(0.149)	-0.704	(0.113)	-0.574	(0.116)
School Northern Territory	0.227	(0.257)	0.272	(0.192)	0.124	(0.194)
School ACT	0.831	(0.232)	0.651	(0.175)	0.936	(0.175)
Catholic School	0.272	(0.063)	0.211	(0.047)	0.176	(0.048)
Private School	0.748	(0.110)	0.553	(0.083)	0.602	(0.084)
Male	-0.245	(0.050)	-0.176	(0.038)	-0.322	(0.038)
μ_1			-3.107	(0.267)	-2.429	(0.261)
μ_2			-2.410	(0.256)	-0.773	(0.257)
μ_3			-1.093	(0.252)	-0.104	(0.257)
μ_4			-0.487	(0.252)	0.789	(0.257)
μ_5			0.597	(0.252)	1.499	(0.258)
μ_6			0.878	(0.252)		
μ_7			1.459	(0.253)		
μ_8			2.446	(0.260)		
μ_9			2.960	(0.276)		
Number of observations	3352		3352		3352	
P-value Year Born Dummies	0.000		0.000		0.000	
Log Likelihood	-5815.51		-5428.54		-4815.46	
(Pseudo) R^2	0.2382		0.0761		0.0826	

A.4.4 Summary Statistics by Sibling Type

Table 4.25: Summary Statistics by Sibling Type

Variable	Brothers		Sisters		Mixed	
	1196 Observations		620 Observations		1536 Observations	
	Mean	(Std Dev.)	Mean	(Std Dev.)	Mean	(Std Dev.)
Log real hourly wage	1.813	(0.397)	1.792	(0.355)	1.798	(0.380)
Real hourly wage	6.607	(2.603)	6.397	(2.627)	6.488	(2.703)
Age	20.745	(2.440)	21.000	(2.416)	20.896	(2.390)
Australian Born White	0.889	(0.315)	0.869	(0.337)	0.901	(0.299)
Australian Born Non-white	0.012	(0.108)	0.006	(0.080)	0.007	(0.084)
Mother Born Australia	0.707	(0.456)	0.769	(0.422)	0.742	(0.438)
Father Born Australia	0.684	(0.465)	0.710	(0.454)	0.711	(0.453)
English Good (ESL)	0.083	(0.276)	0.052	(0.221)	0.048	(0.214)
English Poor (ESL)	0.003	(0.058)	0.013	(0.113)	0.002	(0.044)
Other City at 14	0.170	(0.376)	0.145	(0.353)	0.196	(0.397)
Country Town at 14	0.163	(0.370)	0.205	(0.404)	0.225	(0.418)
Rural Area at 14	0.093	(0.290)	0.040	(0.197)	0.066	(0.248)
Overseas at 14	0.005	(0.071)	0.015	(0.120)	0.011	(0.105)
Lived with mother only at 14	0.046	(0.210)	0.079	(0.270)	0.057	(0.232)
Lived with father only at 14	0.004	(0.065)	0.021	(0.143)	0.007	(0.084)
Lived with neither parent at 14	0.000	(0.000)	0.003	(0.057)	0.005	(0.067)
Mother Degree	0.023	(0.151)	0.037	(0.189)	0.036	(0.186)
Mother Other Tertiary	0.145	(0.353)	0.081	(0.273)	0.120	(0.325)
Father Degree	0.084	(0.278)	0.103	(0.304)	0.092	(0.289)
Father Other Tertiary	0.082	(0.274)	0.087	(0.282)	0.066	(0.249)
Father Manager/Professional	0.407	(0.492)	0.411	(0.492)	0.365	(0.482)
Father Salesperson/Clerk	0.108	(0.310)	0.077	(0.267)	0.100	(0.300)
Father Tradesperson	0.193	(0.395)	0.205	(0.404)	0.186	(0.389)
Father Manual	0.208	(0.406)	0.187	(0.390)	0.235	(0.424)
Mother Manager/Professional	0.131	(0.338)	0.116	(0.321)	0.124	(0.329)
Mother Salesperson/Clerk	0.170	(0.376)	0.247	(0.431)	0.220	(0.414)
Mother Tradesperson	0.013	(0.111)	0.023	(0.149)	0.022	(0.147)
Mother Manual	0.124	(0.329)	0.110	(0.313)	0.132	(0.338)
Number of siblings	2.656	(1.405)	2.771	(1.612)	2.471	(1.376)
Number of older siblings	1.207	(1.322)	1.387	(1.511)	1.251	(1.241)
School Victoria	0.242	(0.429)	0.300	(0.459)	0.262	(0.440)
School Queensland	0.131	(0.338)	0.129	(0.336)	0.144	(0.351)
School South Australia	0.062	(0.241)	0.100	(0.300)	0.062	(0.241)
School Western Australia	0.084	(0.277)	0.087	(0.282)	0.083	(0.276)
School Tasmania	0.015	(0.122)	0.052	(0.221)	0.032	(0.176)
School Northern Territory	0.003	(0.058)	0.023	(0.149)	0.009	(0.095)
School ACT	0.031	(0.173)	0.000	(0.000)	0.001	(0.036)
Catholic School	0.217	(0.413)	0.189	(0.392)	0.201	(0.401)
Private School	0.051	(0.220)	0.047	(0.211)	0.066	(0.249)
Experience	3.993	(2.198)	3.979	(2.307)	4.061	(2.241)
Years of Education	11.753	(1.487)	12.026	(1.674)	11.833	(1.588)
Highest Qualification:						
Degree	0.048	(0.215)	0.079	(0.270)	0.057	(0.232)
Year 12 & Tertiary	0.074	(0.261)	0.160	(0.367)	0.119	(0.324)
Year 12	0.263	(0.440)	0.253	(0.435)	0.244	(0.430)
Year 11	0.238	(0.426)	0.215	(0.411)	0.218	(0.413)
Year 10	0.349	(0.477)	0.261	(0.440)	0.327	(0.469)
< Year 10	0.028	(0.166)	0.032	(0.177)	0.034	(0.181)
< Year 12 & Tertiary	0.225	(0.418)	0.171	(0.377)	0.204	(0.403)
Male					0.500	(0.500)

Chapter 5

Ability, Family Background, Education and Earnings in Britain

5.1 Introduction

Estimates of the returns to education can be upward or downward biased if no account is taken of the fact that education is not randomly assigned across the population. Education outcomes depend on individual choices, attributes and circumstances and if we do not control for how these decisions are made, then the measured differences in the wages of individuals with different levels of education may over- or under- estimate the true causal effect of education on wage outcomes. These biases arise because of correlation between unobserved individual attributes which determine education decisions and wage outcomes.

It is commonly assumed that the most important unobserved component is unobserved ability and that OLS estimates of the returns to education *overstate* the true returns because of this "omitted ability bias". This arises because the estimation procedure is unable to separate the contribution of unobserved ability to productivity from that made by education and ascribes it all to education. As we saw in Chapter 2, however, a number of recent empirical studies looking at this question, have found that conventional OLS estimates *understate* the returns to education, once account is taken of the correlation between unobserved components of education and wages. This can arise if education is measured with error. As Card points out, however, it can also arise if the estimation procedure being used relies on "interventions" that affect the schooling choices of children from relatively disadvantaged family backgrounds with high discount rates rather than low ability.

For individuals of similar abilities, those with lower discount rates (that is better "access to funds" or more "tastes for education") will choose more schooling. For individuals, with similar discount rates, those with higher ability will choose more schooling. If differences in ability are the key determinants of schooling decisions, then estimates of the returns to schooling which do not take this into account will overestimate the returns to such schooling. If differences in discount rates are the most important determinants, then the opposite is true. In order to estimate the true causal effect of education and earnings we therefore have to firstly identify the sources of variation in observed education choices and then understand the type of variation that is being exploited by particular estimation procedures to obtain "corrected" estimates of the return to education. This is what we attempt to do in this Chapter.

In the thesis so far we have relied on instrumental variable techniques and within-family estimation procedures. A third approach involves directly proxying unobserved individual effects such as unobserved ability. Studies utilising this approach such as Blackburn and Neumark[24] have generally relied on using ability tests or aptitude tests in addition to education variables.

In this Chapter we use an extremely rich British panel data set, the National Child Development Survey (NCDS) which potentially allows us to compare each of these three approaches and look at the implications of different estimation techniques on the estimated causal effect of education on wages.

The NCDS survey is a continuing longitudinal survey of persons living in Great Britain who were born between 3 and 9 March 1958. In this Chapter, we focus on individuals from this cohort who were employees in 1991 when they were aged 33 and look at what factors were influential in determining their educational outcomes and the returns to this education. The NCDS data set has detailed information on parents education and labour market experience over the period 1958 to 1974; educational records from the child's school and teachers when the child was aged 7, 11 and 16; results of verbal and quantitative ability tests taken by the cohort when they were aged 7, 11 and 16; as well as entire labour market histories for the cohort dating from the time they first entered the labour market up until 1991.

In this Chapter we use this data to look at a number of issues. We begin by ignoring our measures of ability, and once again use instrumental variable techniques to correct for biases caused by correlation between unobserved determinants of wages and schooling. We follow the approach we used in Chapter 3 and again use family background variables as instruments for education. This again includes variables identifying the number siblings and number of older siblings an individual has. The NCDS also has other information about the family including the sex composition of siblings which was found to be important for women in the US study by Butcher and Case [45]. In Britain we find no significant effect of birth order on educational outcomes, controlling for family size, and other socio-economic characteristics. We do find, however, that women who only have either only male siblings or only female siblings, do significantly better than women who do not, controlling for family size. This effect is not found for males.

We also utilise information obtained from the individuals' school teacher at the age of seven. The teacher was asked to rate the interest shown by each of the parents in the child's education at that time. Individuals whose parents showed interest in their education at that early age, have significantly better educational outcomes than individuals whose parents showed little or no interest in their education at that age. This results holds for both men and women. Since sibling sex composition affects women's educational outcomes and parent's early interest in their child's education affects both women's and men's educational outcomes and both can be argued to be unrelated to other determinants of wages, we use these as instruments for education in our wage equations. Our IV estimates of the returns to education once again suggest that OLS estimates that do not take into account these other correlated individuals effects significantly underestimate the returns to education. The instrumental variables we use to explain variations in educational outcomes are generally variables which measured things like access to funds (for example, whether the family was in serious financial trouble in 1974) and tastes for education (for instance, the interest shown by parents in their child's education at the age of seven), though this is not entirely true (for example parental education my be more related to ability).

We then move on to consider the extent of omitted ability bias in ordinary least squares estimates of the returns to education. We use the ability tests undertaken by the individuals at the age of seven as a proxy for unobserved ability. We find that our proxies of ability are important determinants of the level of earnings received by individuals, and that conventional estimates of the returns to education which do not control for this, over-estimate the returns to education. These measures of ability are positively correlated with both schooling and wages, and estimates which do not take this correlation into account underestimate the returns to education.

When we take into account the effects of *both* omitted ability and other correlated individual effects the estimated returns to education are above OLS estimates, though (marginally) below IV estimates which do not include measures of ability.

We then go on to look at whether individuals with different abilities have different returns to education and qualifications. We find no evidence of this in our sample. We also attempt to control for possible measurement error in our measures of ability, but it appears that our ability tests are good proxies of unobserved ability.

The data also has potential to exploit fixed effect estimation techniques. Because the NCDS sample is a census of all individuals born in one week in March 1958 it includes a number of twins and triplets. This means that we also can use within family fixed effect estimation procedures. Unfortunately, however, the twin and triplet sample by 1991 is very small[1] and it is difficult to draw any definitive conclusions from results based on such a small sample. A significant proportion of our sample who were in work in 1981 at the age of 23, have however, undertaken further education between 1981 and 1991. In this Chapter, however, we concentrate solely on education undertaken predominantly before individuals entered the labour market. The returns to subsequent education and training are the focus of the next Chapter.

In section 2 we look more closely at the NCDS data used in our analysis. In section 3 we outline our estimation methodology. In section 4 the results of our analysis are discussed. In section 5 we look at education and gender wage differentials and conclusions are offered in section 6.

5.2 The NCDS Data

5.2.1 Introduction

The National Child Development Survey (NCDS) is a continuing longitudinal survey of persons living in Great Britain who were born between 3 and 9 March, 1958. As mentioned in Chapter 1, there have been 5 waves of the NCDS, the last survey having been undertaken in 1991 when the cohort members were 33 years of age.

In this Chapter we concentrate on only those individuals who participated

[1]Our final sample consists of 3512 employees in 1991 and this sample only contains 16 pairs of twins.

in four of the five waves of the NCDS[2]. We exclude any individuals who were not employees in 1991. We also exclude people who were employees but for who we do not have valid hourly wages information in 1991.

5.2.2 Variables used in the analysis

Education and Ability Variables

The NCDS has information on the individuals highest school qualification and post-school qualification as at 1981 which we view as "education" or "schooling". It also has the results from verbal and non-verbal ability tests undertaken when the person was seven, eleven and sixteen as well as the information on the years of full-time education.

In looking at the returns to education we use two measures of education. The first measures years of full-time education and is constructed on the assumption that the individual commenced full-time education in September 1963 when they were aged 5[3]. In constructing this measure we use the monthly economic activity information available from the NCDS4 survey. The second involves identifying a persons highest education qualification. A lot of men in our sample undertook apprenticeship qualifications which were largely taken on a part-time basis. Our measure of years of full-time education will not capture this part-time study. The NCDS, however, also gives us information on the persons highest school and post-school qualification as at 1981. We use this information to identify a person's highest educational qualification and follow as closely as possible the schema of Schmitt [143] which has subsequently been used by the OECD [134]. These were outlined in Chapter 2 in Table 2.1. Our education measure based on highest qualifi-

[2]We do not use information from the second wave of the NCDS when the individual was aged 11.

[3]The NCDS1 survey also identifies when individuals commenced part-time and full-time "school". These variables suggest that a relatively high proportion of the sample begin school at or before the age of four and also have a large number of missing variables. We therefore instead choose to use the usual Mincer[128] approach.

cation are once again clearly ordered and a full description of our education variables is contained in Table 5.1[4].

Table 5.1: Description of Highest Education Qualification Variables

Variable	Description
Highest Qualification at age 23 in 1981:	
Degree	University or CNAA first degree, CNAA Post-graduate Diploma, or University or CNAA Higher Degree.
Higher Vocational	Highest Vocational: Full professional qualification, part of a professional qualification, Polytechnic Diploma or Certificate (not CNAA validated), University or CNAA Diploma or Certificate, Nursing qualification including nursery qualification, non-graduate teaching qualifications, Higher National Certificate (HNC) or Diploma (HND), BEC/TEC Higher Certificate or Higher Diploma, City and Guilds Full Technological Certificate.
A Levels	At least one GCE A Level, Scottish Leaving Certificate (SLC), Scottish Certificate of Education (SCE), Scottish University Preliminary Examination (SUPE) at Higher Grade, Certificate of Sixth Year Studies.
Middle Vocational	Middle Vocational: City and Guilds Advanced or Final, Ordinary National Certificate (ONC) or Diploma (OND), BEC/TEC National, General or Ordinary.
5+ O Levels	At least five GCE O Level passes or grades A–C, or CSE Grade 1 or equivalent.
Lower Vocational	Lower Vocational: City and Guilds Craft or Ordinary, a Royal Society of Arts (RSA) awards, stage 1, 2 or 3 or other commercial or clerical qualifications
O Levels	At least one GCE O Level passes or grades A–C, or CSE Grade 1 or equivalent.
Other	Miscellaneous Qualifications: All other courses leading to some sort of qualification which are not identified above including CSE grade 2–5 or equivalent and miscellaneous apprenticeship qualifications.
None	No qualifications including those with no formal schooling.

We also construct measures of verbal and mathematic ability which are based on ability tests undertaken when the child was aged seven. We use the seven year old test results, as these are much less likely to be affected by knowledge gained at school. From these verbal and mathematic ability tests we construct 10 dummy variables which rank the individual's results in each of the tests by quintiles[5].

[4]Unlike Schmitt, we do not separately identify teaching qualifications and these are included in the highest vocational qualifications if they did not lead to a degree. We also do not have a category of O Levels plus comercial/clerical. People with commercial or clerical qualifications are included in the Lower Vocational category.

[5]We choose quintiles, as 20 per cent of individuals in 1965 when the tests were undertaken obtained maximum marks in the verbal ability test. The quintiles refer to quintiles at the time the test was taken and not in our final sample.

School and Family Background Variables

We use data from the first wave of the NCDS to construct dummy variables identifying the teacher's assessment of the child's numerical and reading ability at age 7, as well as the teacher's assessment of the interest shown by the mother and father in the education of the child at that age.

We use the data from the third wave of the survey to construct variables identifying the respondent's parents' social class; the years of full-time education undertaken by the child's mother and father at that age[6]; variables identifying individuals who had no mother or father at that age; whether the family was experiencing financial difficulties in 1974[7]; the number of siblings and older siblings the respondent had; whether the respondent had only brothers or sisters and finally variables identifying the region in which the child lived in 1974.

Wage, Experience and Regional Variables

We use data from the NCDS5 survey to construct real hourly gross wage data measured in 1985 prices. We limit our sample to individuals who are employees at the time of the 1991 survey. We also use the survey to construct regional dummy variables[8]. From the NCDS5 and NCDS4 monthly work history data we construct a measure of years of actual labour market

[6]The variable measures the years of full-time education undertaken by the child's mother and father figure at the age of 16. This is constructed from a variable which identifies the age at which the parent's left full-time education, assuming they started school at the age of five. If there is no mother or father figure, then parental years of education are set to zero. We separately identify individual's who have no mother or father figures.

[7]Following Micklewright[122], this identifies individual's who received free school meals in 1974 or whose parents were seriously troubled financially in the year prior to the 1974 survey.

[8]The regional data in NCDS5 is still being constructed and cleaned up and the regional data which has been released has missing observations for around one third of the sample. We use regional information from NCDS4 for these individuals.

experience[9].

The Final Sample

We drop individuals who have missing observations for any of these variables. This leaves us with a final sample of 1932 males and 1580 females. Summary Statistics for these individuals are given in Table 5.19 in Appendix A.5.1. These show that the sample used in this Chapter under-represents individuals in the bottom quintiles of the verbal and arithmetic ability tests undertaken when the child was 7.

5.3 Methodology

5.3.1 Omitted Ability and the Returns to Education

We start with the two equation system

$$w_i = s_i'\beta_1 + X_i'\beta_2 + A_i'\alpha + \varepsilon_i \tag{5.1}$$

$$s_i = Z_i'\gamma + v_i \tag{5.2}$$

where s_i is years of full-time education, w_i is the log of the real hourly wage rate, A_i is unobserved ability, ε_i represents other unobserved individual effects which may be correlated with education, X_i and Z_i are vectors of exogenous observed individual characteristics, β_1 is the return to education, α the return to ability, and $u_i = A_i'\alpha + \varepsilon_i$ and v_i are a pair of residuals. OLS estimation of equation (5.1) gives rise to a unbiased estimate of the return to education if u_i and v_i are uncorrelated, that is if s_i is exogenous in equation (5.1) ($E(s_i(A_i'\alpha+\varepsilon_i)) = 0$). If unobserved schooling and ability are positively correlated, then this clearly is not going to hold and OLS will overestimate the true returns to schooling.

[9] The experience variable is a measure of months in the labour market since January 1974 divided by 12.

One approach which has been used in the literature to obtain consistent estimates of the returns to schooling is to proxy the correlated unobserved fixed effect. Suppose we can model the innate ability as

$$E(A_i|P_i, s_i, X_i) = P_i'\pi \tag{5.3}$$

where P_i are observable variables which are thought to proxy unobserved ability (for example results of ability tests). Then conditional on these variables, $A_i - E(A_i|P_i, s_i, X_i)$ will be uncorrelated with the schooling variable which appears in the wage equation. Thus we can instead estimate the following equation consistently by OLS

$$w_i = s_i'\beta_1 + X_i'\beta_2 + P_i'\beta_3 + \widetilde{u}_i \tag{5.4}$$

if $E(\widetilde{u}_i, s_i) = 0$ where $\widetilde{u}_i = (A_i - E(A_i|P_i, s_i, X_i))'\alpha + \varepsilon_i$. The ability to proxy the unobserved fixed effect is clearly going to depend on the quality of the data being used. The problem with this approach, as pointed out by Welch [160] and Griliches [82], is that the more variables we include in our earnings equation to overcome biases related to missing ability variables, the more we raise problems of biases arising from measurement error. This is considered in more detail below.

5.3.2 Other Correlated Individual Effects

Clearly OLS estimation of equation 5.4 will only be consistent if there are no other unobserved individual effects correlated with schooling (or indeed any right hand side variable), that is if $E(s_i\varepsilon_i) = 0$. If this does not hold, then we will once again have to rely on other estimation procedures. One possibility would be to use a fixed effects estimator since we have wage information when the individual was 23 and 33. The problem for us here is that we are purely focusing on the returns to education obtained up until the time the individual was 23 and our wage observation is not recorded before these qualifications were completed. In the next Chapter we look at the returns to work related training and qualifications obtained after the age of 23 for the same sample used in this Chapter and this allows us to use a fixed effect approach.

In this Chapter we therefore once again rely on instrumental variable techniques. As with our Australian sample, we use our extensive information on family characteristics as instruments for education. These include variables identifying the teachers assessment of the child's reading and arithmetic ability at age 7; the teachers assessment of the mother's and father's interest in the child's education at age 7; variables measuring father's and mother's years of full-time education; mother's and father's social class when the individual was age 16; whether the family was experiencing financial difficulties in 1974; the region in which the family lived in 1974; the number of siblings and number of older siblings the individual had at age 16; and whether the individual has brothers or sisters only. Our additional exogenous explanatory variable in the wage equation (X_i), consist of gender and regional dummy variables[10]. Given that this cohort were born in exactly the same week of 1958 we cannot include age variables or potential labour market experience variables. We do, however, have information on the individual's actual labour market experience which is constructed from monthly economic activity records obtained from the NCDS4 and NCDS5 data. For our years of full-time education variable we carry out IV estimation of equation treating schooling as endogenous (5.1)[11].

For our highest qualification variable we exploit the fact that this measure

[10] In earlier analysis we also included a variable identifying race, however, the number of non-white individuals in our NCDS sample is extremely small.

[11] This is equivalent to estimating the following wage equation

$$\ln w_i = \beta_1' s_i + \beta_2(X_i) + \alpha\widehat{v}_i + \varepsilon_i$$

where $\widehat{v}_i$ are the residuals from OLS estimation of equation (5.2) and $E(s_i\varepsilon_i) = 0$ by construction. A Hausman t test of the exogeneity of schooling is given by testing $\alpha = 0$ (see Smith and Blundell[148]).

of educational outcome is ordered and use a latent variable model of the form

$$s_i^* = Z_i'\gamma + v_i \tag{5.5}$$

where

$$s_{ij} = 1 \text{ if } \mu_{j-1} < s_i^* \leq \mu_j \tag{5.6}$$

where $j = 0, 1, 2, 3...8$ and s_{ij} is a dummy variables identifying a person with highest qualification j, and $\mu_{j-1} < \mu_j$. The education equations are now estimated as ordered probits and the parameter estimates are used to calculate the usual Heckman [97] selection adjustment term for our ordered qualification variables

$$\widehat{\lambda}_{qi} = \frac{\phi(\widehat{\mu}_j - Z_i'\widehat{\gamma}) - \phi(\widehat{\mu}_{j+1} - Z_i'\widehat{\gamma})}{\Phi(\widehat{\mu}_{j+1} - Z_i'\widehat{\gamma}) - \Phi(\widehat{\mu}_j - Z_i'\widehat{\gamma})} \tag{5.7}$$

where the $\widehat{\mu}_j$'s and $\widehat{\gamma}$ are the estimates obtained from the ordered probit maximum likelihood procedures, and $\phi(.)$ and $\Phi(.)$ are the normal probability distribution and normal cumulative distribution functions respectively. We can then estimate the following wage equation

$$w_i = s_i'\beta_1 + X_i'\beta_2 + P_i'\beta_3 + \varphi\widehat{\lambda}_{qi} + \varepsilon_i \tag{5.8}$$

where s_i is now a vector of dummy variables identifying the person's highest qualification. In this formulation our standard errors are corrected to take account of the generated regressor $(\widehat{\lambda}_{qi})$ in the equation[12].

5.3.3 Measurement Error and Proxying Ability

To discuss this issue let us consider the simplified wage equation of the form

$$w_i = \beta_1 s_i + \alpha A_i + \varepsilon_i \tag{5.9}$$

where years of schooling (s_i) is observed, but innate ability (A_i) is not. Instead of A_i we observe a proxy P_i which is measured with error, that is

$$P_i = A_i + e_i \tag{5.10}$$

[12] See Arrelano and Meghir [4].

where e_i is assumed to be uncorrelated with A_i, s_i and η_i. If we omit the variable A_i from equation (5.9) and estimate the returns to schooling by OLS, the probability limit is given by

$$p\lim \beta_1^{OLS} = \beta_1 + \alpha \frac{\sigma_{sA}}{\sigma_s^2} \tag{5.11}$$

where σ_s^2 denotes the population variance of schooling and σ_{sA} the population covariance between schooling and ability. If instead we use a proxy for ability and substitute this in for A_i in equation (5.9) then the probability limit of the OLS estimate of the return to training is now given by (see Maddala [119, p. 396])

$$p\lim \beta_1^{PR} = \beta_1 + \alpha \frac{\sigma_{sA}}{\sigma_s^2} \left[\frac{\sigma_e^2}{\sigma_e^2 + \sigma_A^2(1-\rho^2)} \right] \tag{5.12}$$

where ρ is the correlation between schooling and ability. Since the term in square brackets is less than one, this suggests that the bias in the estimate of the return to schooling is reduced by including a proxy, even if it is relatively poor. If, however, the proxy is a dummy variable this result is no longer necessarily true (see Maddala [118, pp. 161-162]).

Welch [160] also has shown that this reduction in bias does not necessarily follow if schooling is also measured with error. If this is the case then there is an upward bias due to missing ability and a downward bias due to measurement error in schooling. The same is true if we include a proxy of ability in our equation. Thus if both schooling and ability are measured with error, then it may be the case that the using a proxy to correct for omitted ability bias, might be at the expense of increasing measurement error bias. The full derivation of this result is given in Maddala [118, pp. 304-305]. This suggests that once again we may need to rely on instrumental variables techniques.

To carry out IV estimation we once again need a set of instruments which are correlated with the true measures of education and ability and uncorrelated with the measurement errors. Following Griliches and Mason[86] and Blackburn and Neumark[24], we use our instruments for education also as instruments for our measures of ability. These instruments include dummy variables identifying the teacher's assessment of the student's mathematical and reading ability at the age of seven. For the specification where we measure education by the highest obtained qualification we can estimate the following wage equations

$$w_i = s_i'\beta_1 + X_i'\beta_2 + P_i'\beta_3 + \varphi_1\widehat{\lambda}_{qi} + \widehat{\lambda}_{ai}'\varphi_2 + \varepsilon_i \tag{5.13}$$

where $\widehat{\lambda}_{ai}' = (\widehat{\lambda}_{mai}, \widehat{\lambda}_{vai})$ is a vector containing the pair of selection terms from our reduced form arithmetic and verbal ability ordered probits[13]. Again in this formulation we have a direct Hausman type t test of whether we have a measurement error problem with our proxies of ability.

5.3.4 Do returns to schooling vary by ability?

In the earnings equations set out above, we only allow our proxies of ability to affect the level of earnings received by individuals. We do not allow for the possibility that the returns to schooling may also vary for individuals with different abilities. We can easily extend our model to explicitly allow for this possibility. For example, we can split our sample into high ability, middle ability and low ability groups based on the ability tests undertaken at the age of seven and see if the returns to education vary for these different groups of individuals. We can then replace equation (5.13) with an equation of the form

$$w_i = s_{hi}'\beta_{h1} + s_{mi}'\beta_{m1} + s_{li}'\beta_{l1} + X_i'\beta_2 + P_i'\beta_3 + \widehat{\lambda}_{qi}\varphi_1 + \widehat{\lambda}_{ai}'\varphi_2 + \varepsilon_i \tag{5.14}$$

and test whether the return to education are the same for individuals with different measured abilities at the age of seven. We can also extend this to see whether returns to experience vary for individuals with different abilities.

[13]The ordered probits are carried out on the variables identifying the individual's quintile for both the verbal and arithmetic ability test undertaken at the age of seven.

5.3.5 Education and Gender Wage Differentials

Again, as we did in Chapter 3, we can decompose the mean difference in the observed wages of men and women in terms of log differences into two effects

$$\widehat{g} = (\overline{x}_m - \overline{x}_f)'\widehat{\beta}_m + \overline{x}_f(\widehat{\beta}_m - \widehat{\beta}_f) = \widehat{g}_c + \widehat{g}_p \qquad (5.15)$$

where $\overline{x}_m$ and $\overline{x}_f$ are vectors containing the means of all the explanatory variables in our male and female wage equations (except selection terms) and $\widehat{\beta}_m$ and $\widehat{\beta}_f$ are the corresponding estimated coefficient vectors. The first term is an estimate of the mean difference in observed wages which arises because men and women have different observed characteristics, for instance education and labour market experience. The second is the differences in observed wages which is a result of men and women being "paid" differently for a given set of characteristics. Again, the mean gender wage gap of any subgroup s, of our sample, for instance individuals with a particular educational qualification, can be calculated by replacing the mean characteristics of males and females with those of the subgroup s of interest, $\overline{x}'_{sm}$ and $\overline{x}'_{sf}$ in equation (5.15).

5.4 Results

5.4.1 Determinants of Education Outcomes

From our data we have constructed two measures of educational outcomes. The first is years of full-time education and the second involved identifying the highest qualification a person has received. In Tables 5.2 and 5.3 we present the results of our various education equations for males and females respectively. Results for the whole sample are given in Table 5.20 in Appendix A.5.2. In the columns 1 and 2 of these tables we present the results from our reduced form years of education regression. In the first column we exclude our quintile ability measures and in the second column we include them. In the third and fourth columns we present analogous results of our highest qualification ordered probit equation.

All four columns in Table 5.2 give broadly similar results as to the determinants of educational outcomes for men. It is clear that more able men do significantly better than less able men. We see that men who had good number and reading skills at the age of seven do significantly better than those with less developed skills. The individual's ability as assessed by their teacher at seven remains significant when we also include the results of the verbal and numeric ability tests. It is also true that sons whose father or mother were very interested in their education at the age of seven have significantly better outcomes than those for who this was not true.

Children with more educated father's and mother's have better educational outcomes than children from less well educated parent's. For men with no father figures, they on average achieved educational outcomes similar to men's whose father had 8 years of education[14]. Men whose fathers who worked in more highly skilled occupations do significantly better than sons whose fathers work in relatively unskilled jobs. Mother's occupational status does not, however, appear to be important for men's educational outcomes, though there is some evidence that men whose mother was in a low skilled jobs in 1974 do worse than those whose mother was not working or was in a relatively skilled jobs.

Family size, measured by the number of siblings, has a negative effect on men's educational outcomes, but order of birth plays no significant role for our British cohort. The composition of the man's sibship is also not important[15].

[14]For children with no mother of father figure, the years of education variables is set to zero. By dividing the coefficient on the dummy variable for no father's or no mother's by the coefficient on the effect of an extra year of parental education we can estimate, on average, how children with no mother or father figues, compare to children with mother's or father's who have undertaken education.

[15]We experimented with a number of measures of family composition, including presence of any brothers or sisters and proportion of brothers and sisters. These were all insignificant

Table 5.2: The Determinants of Male Education Outcomes

Variable	Years of Full-time Education				Highest Qualification			
	Coef.	(S.E.)	Coef.	(S.E.)	Coef.	(S.E.)	Coef.	(S.E)
Constant	8.226	(0.397)	8.186	(0.403)				
Maths ability:								
2nd quintile			0.003	(0.141)			0.120	(0.087)
3rd quintile			0.073	(0.145)			0.210	(0.090)
4th quintile			0.172	(0.152)			0.159	(0.093)
5th quintile			0.404	(0.162)			0.337	(0.099)
Verbal ability:								
2nd quintile			0.240	(0.141)			0.196	(0.087)
3rd quintile			0.222	(0.160)			0.233	(0.098)
4th quintile			0.434	(0.172)			0.375	(0.105)
5th quintile			0.742	(0.187)			0.382	(0.114)
Teacher's rating:								
Avid reader	1.161	(0.219)	0.671	(0.243)	0.670	(0.134)	0.396	(0.149)
Above average reader	0.815	(0.148)	0.420	(0.176)	0.560	(0.090)	0.307	(0.107)
Average reader	0.280	(0.120)	0.111	(0.137)	0.357	(0.073)	0.202	(0.084)
Excellent number skills	0.805	(0.220)	0.500	(0.232)	0.744	(0.134)	0.549	(0.143)
Good number skills	0.491	(0.140)	0.271	(0.151)	0.627	(0.085)	0.498	(0.092)
Average number skills	0.154	(0.113)	0.029	(0.119)	0.342	(0.069)	0.256	(0.073)
Father's interest in edn:								
Very interested	0.311	(0.127)	0.276	(0.127)	0.235	(0.077)	0.217	(0.077)
Some interest	0.168	(0.109)	0.155	(0.109)	0.092	(0.066)	0.077	(0.066)
Mother's interest in edn:								
Very interested	0.306	(0.143)	0.306	(0.142)	0.139	(0.087)	0.137	(0.087)
Some interest	0.120	(0.123)	0.119	(0.123)	0.187	(0.075)	0.193	(0.075)
Father's years of education	0.124	(0.028)	0.122	(0.028)	0.067	(0.017)	0.066	(0.017)
No Father Figure	1.032	(0.359)	1.020	(0.358)	0.712	(0.221)	0.696	(0.222)
Mother's years of education	0.208	(0.034)	0.200	(0.034)	0.080	(0.021)	0.077	(0.021)
No Mother Figure	1.509	(0.492)	1.386	(0.491)	0.544	(0.302)	0.468	(0.303)
Father's social class 1974:								
Prof/Intermediate	0.714	(0.206)	0.672	(0.205)	0.516	(0.127)	0.478	(0.127)
Skilled non-manual	0.553	(0.221)	0.530	(0.220)	0.432	(0.136)	0.412	(0.136)
Skilled manual	0.083	(0.190)	0.083	(0.190)	0.273	(0.118)	0.265	(0.118)
Semi-skilled	-0.007	(0.210)	-0.015	(0.209)	0.087	(0.130)	0.071	(0.130)
Unskilled	-0.187	(0.299)	-0.169	(0.298)	-0.204	(0.188)	-0.204	(0.189)
Mother's social class 1974:								
Prof/Intermediate	-0.186	(0.142)	-0.170	(0.142)	-0.140	(0.087)	-0.139	(0.087)
Skilled non-manual	0.072	(0.113)	0.038	(0.113)	-0.059	(0.069)	-0.082	(0.069)
Skilled manual	-0.256	(0.206)	-0.254	(0.205)	-0.152	(0.125)	-0.144	(0.125)
Semi-skilled	-0.294	(0.115)	-0.301	(0.114)	-0.082	(0.070)	-0.091	(0.070)
Unskilled	-0.172	(0.166)	-0.180	(0.166)	-0.029	(0.100)	-0.033	(0.101)
Financial Difficulties 1974	-0.069	(0.149)	-0.050	(0.148)	-0.136	(0.091)	-0.125	(0.091)
Number of siblings	-0.084	(0.038)	-0.075	(0.038)	-0.065	(0.023)	-0.061	(0.024)
Number of older siblings	0.014	(0.043)	0.004	(0.043)	-0.006	(0.027)	-0.013	(0.027)
Brothers only	-0.141	(0.102)	-0.118	(0.101)	0.003	(0.062)	0.016	(0.062)
Sisters only	-0.138	(0.105)	-0.146	(0.104)	-0.034	(0.064)	-0.038	(0.064)
μ_1					1.284	(0.251)	1.407	(0.257)
μ_2					1.508	(0.252)	1.633	(0.258)
μ_3					1.900	(0.252)	2.028	(0.258)
μ_4					2.227	(0.252)	2.358	(0.259)
μ_5					2.465	(0.253)	2.598	(0.259)
μ_6					3.060	(0.255)	3.197	(0.261)
μ_7					3.338	(0.256)	3.478	(0.262)
μ_8					3.802	(0.258)	3.948	(0.265)
Number of observations	1932		1932		1932		1932	
P-value regional dummies	0.7756		0.8125		0.052		0.0843	
Log Likelihood	-3778.33		-3759.98		-3740.17		-3722.86	
(Pseudo) R^2	0.3070		0.3201		0.0884		0.0926	

Table 5.3: The Determinants of Female Education Outcomes

Variable	Years of Full-time Education				Highest Qualification			
	Coef.	(S.E.)	Coef.	(S.E.)	Coef.	(S.E.)	Coef.	(S.E)
Constant	8.153	(0.450)	8.108	(0.456)				
Maths ability:								
2nd quintile			0.135	(0.142)			0.109	(0.094)
3rd quintile			0.212	(0.147)			0.253	(0.096)
4th quintile			0.252	(0.150)			0.170	(0.097)
5th quintile			0.390	(0.162)			0.327	(0.105)
Verbal ability:								
2nd quintile			-0.001	(0.181)			0.207	(0.124)
3rd quintile			0.112	(0.190)			0.311	(0.127)
4th quintile			0.340	(0.196)			0.490	(0.131)
5th quintile			0.564	(0.208)			0.533	(0.138)
Teacher's rating:								
Avid reader	1.399	(0.226)	0.931	(0.256)	1.276	(0.148)	0.911	(0.168)
Above average reader	0.782	(0.174)	0.405	(0.205)	0.944	(0.116)	0.615	(0.135)
Average reader	0.278	(0.151)	0.107	(0.169)	0.532	(0.102)	0.329	(0.114)
Excellent number skills	0.258	(0.282)	0.050	(0.290)	0.462	(0.182)	0.306	(0.188)
Good number skills	0.073	(0.148)	-0.105	(0.157)	0.368	(0.094)	0.229	(0.101)
Average number skills	0.131	(0.112)	0.034	(0.116)	0.291	(0.072)	0.212	(0.075)
Father's interest in edn:								
Very interested	0.067	(0.129)	0.032	(0.129)	0.133	(0.082)	0.107	(0.082)
Some interest	0.164	(0.118)	0.144	(0.118)	0.006	(0.075)	-0.004	(0.076)
Mother's interest in edn:								
Very interested	0.322	(0.156)	0.310	(0.156)	0.231	(0.101)	0.219	(0.102)
Some interest	-0.149	(0.139)	-0.143	(0.139)	0.114	(0.091)	0.112	(0.092)
Father's years of education	0.103	(0.029)	0.095	(0.029)	0.079	(0.019)	0.073	(0.019)
No Father Figure	0.979	(0.372)	0.886	(0.372)	0.697	(0.241)	0.620	(0.243)
Mother's years of education	0.279	(0.034)	0.279	(0.034)	0.106	(0.022)	0.109	(0.022)
No Mother Figure	2.485	(0.475)	2.494	(0.473)	1.182	(0.306)	1.213	(0.307)
Father's social class 1974:								
Prof/Intermediate	0.434	(0.212)	0.404	(0.212)	0.199	(0.137)	0.163	(0.139)
Skilled non-manual	-0.256	(0.232)	-0.271	(0.232)	-0.056	(0.150)	-0.082	(0.151)
Skilled manual	-0.283	(0.196)	-0.274	(0.195)	-0.132	(0.127)	-0.140	(0.128)
Semi-skilled	-0.359	(0.221)	-0.354	(0.220)	-0.226	(0.144)	-0.236	(0.145)
Unskilled	-0.327	(0.286)	-0.360	(0.285)	-0.224	(0.189)	-0.253	(0.190)
Mother's social class 1974:								
Prof/Intermediate	0.551	(0.153)	0.535	(0.152)	0.307	(0.098)	0.304	(0.099)
Skilled non-manual	-0.205	(0.123)	-0.238	(0.123)	0.060	(0.078)	0.034	(0.079)
Skilled manual	-0.351	(0.199)	-0.369	(0.198)	0.046	(0.126)	0.033	(0.126)
Semi-skilled	-0.130	(0.123)	-0.123	(0.122)	-0.007	(0.079)	-0.003	(0.079)
Unskilled	-0.193	(0.181)	-0.208	(0.181)	-0.133	(0.118)	-0.139	(0.119)
Financial Difficulties 1974	-0.235	(0.152)	-0.212	(0.152)	-0.326	(0.101)	-0.309	(0.101)
Number of siblings	-0.062	(0.038)	-0.052	(0.037)	-0.066	(0.025)	-0.059	(0.025)
Number of older siblings	0.043	(0.045)	0.029	(0.045)	0.036	(0.029)	0.027	(0.030)
Brothers only	0.262	(0.109)	0.255	(0.109)	0.120	(0.070)	0.110	(0.070)
Sisters only	0.117	(0.111)	0.103	(0.111)	0.142	(0.070)	0.132	(0.071)
μ_1					1.827	(0.300)	2.002	(0.307)
μ_2					1.980	(0.300)	2.159	(0.308)
μ_3					2.709	(0.302)	2.899	(0.310)
μ_4					2.911	(0.303)	3.104	(0.310)
μ_5					3.298	(0.304)	3.496	(0.312)
μ_6					3.506	(0.306)	3.705	(0.313)
μ_7					3.736	(0.307)	3.937	(0.314)
μ_8					4.346	(0.310)	4.555	(0.317)
Number of observations	1580		1580		1580		1580	
P-value regional dummies	0.007		0.022		0.304		0.376	
Log Likelihood	-3022.56		-3009.47		-2870.73		-2851.55	
(Pseudo) R^2	0.3459		0.3567		0.1116		0.1175	

The results for women reported in Table 5.3. For women, the years of education and highest qualification specifications are again broadly consistent. In the years of education specification, ability is again an important determinant of years of education, though not all measures are significant. In the highest qualifications specifications they appear more significant. The teacher's assessment of the women's reading ability at the age of seven appears to be particularly important. Mother's interest in the child's education at the age of seven is significant for women, however, father's interest does not appear to be important for daughters. Mother's and father's years of education are again important for women, and women whose father and mother were in the highest social class do significantly better than those whose parents were not. Women whose families were in serious financial trouble do worse in the highest educational specification, as do women who come from a large family. For women, the composition of the family also seems important. In the years of education specification, women who have only brother's do significantly better than those who do not. In the highest qualification specification women who have only brothers or only sisters do better than women for who this was not true[16].

In Table 5.20 of Appendix A.7.3 we report the results for the male and female sample as a whole. The results from this table suggest that the years of education outcomes of women are higher than those of men in our sample, but the highest qualification outcomes are not as good as those of men. This may reflect the fact that our years of education variable only measures years of full-time years of education and a significant proportion of our male sample has undertaken part-time apprenticeship qualifications which will not

in our male education equations. When we excluded parental interest variables in our reduced form education equations, birth order effects became significant and negative for men.

[16] Again we tried a number of measures of family composition such us presence of any brothers or any sisters and proportion of brothers and sisters, however, brothers only and sisters only were the only variables found to be significant in our women's education equations, which also controlled for family size.

be picked up by this measure of education.

5.4.2 Estimates of the Returns to Education

The Returns to Years of Education

Table 5.4 reports the results for men of our OLS and IV estimation procedures. In the first column we report the OLS estimates of the returns to education when we do not include actual labour market experience. The second column reports our OLS results when we include actual labour market experience. The third and fourth columns present the corresponding IV estimates for the specifications with and without labour market experience[17]. In these equations our instruments for years of schooling are family characteristics such as parent's education and social class, teachers assessment of the child's ability and of the parent's interest in the child's education at the age of seven, as well as family composition variables such as the number of siblings, the number of older siblings and whether the child had brothers or sisters only. It of course could be argued, that some of these variables legitimately belong in a wage equation, even controlling for education. We will look at the sensitivity of our IV estimates to our identification assumptions later.

Table 5.4: Male Returns to Education

Variable	Ordinary Least Squares				Instrumental Variables			
	Coef.	(S.E.)	Coef.	(S.E.)	Coef.	(S.E.)	Coef.	(S.E)
Constant	0.982	(0.063)	-1.020	(0.173)	0.359	(0.098)	-1.503	(0.190)
Years of Education	0.069	(0.004)	0.143	(0.007)	0.119	(0.007)	0.186	(0.010)
Experience			0.071	(0.006)			0.068	(0.006)
Education residuals					-0.071	(0.009)	-0.065	(0.009)
Number of observations	1932		1932		1932		1932	
P-value regional dummies	0.000		0.000		0.000		0.000	
Log Likelihood	-805.76		-739.90		-772.87		-710.83	
R^2	0.2018		0.2544		0.2285		0.2765	

The OLS estimate of the return to years of education is 6.9 per cent

[17]In all these specifications we are treating actual labour market experience as exogenous. Hausman tests of the endogeneity of labour market experience, using the same instruments as for years of education, were found to be insignificant.

in the specification where we do not include labour market experience and 14.3 per cent in the specification where we do. The return to labour market experience in 7.1 per cent. Therefore the benefit of doing an extra year of education, compared to a years labour market experience is 7.2 per cent. Our IV estimates of the returns to education is 11.9 per cent in the equation in which we do no included experience and 18.6 per cent in the equation in which we do. Again the actual benefit of doing an extra years education compared to a year in the labour market is very similar in both specifications. This suggests that including actual labour market experience for this ages specific age cohort of men is not important. We see that in both our IV equations these wage equations, the residuals from the education equations are negative and significant, suggesting that years of education is endogenous[18]. Our OLS estimates of the returns to education are similar to those found by Harmon and Walker[90] using FES data, however our IV estimates are somewhat smaller. They found a corrected estimate of the return to schooling of 15.3 per cent.

Table 5.5: Female Returns to Education

Variable	Ordinary Least Squares				Instrumental Variables			
	Coef.	(S.E.)	Coef.	(S.E.)	Coef.	(S.E.)	Coef.	(S.E)
Constant	0.121	(0.079)	-1.040	(0.089)	-0.359	(0.123)	-1.347	(0.118)
Years of Education	0.111	(0.005)	0.143	(0.005)	0.149	(0.009)	0.169	(0.009)
Experience			0.056	(0.003)			0.055	(0.003)
Education residuals					-0.057	(0.011)	-0.040	(0.010)
Number of observations	1580		1580		1580		1580	
P-value regional dummies	0.000		0.000		0.000		0.000	
Log Likelihood	-799.94		-638.18		-784.93		-629.60	
R^2	0.2816		0.4146		0.2952		0.4210	

The corresponding results for females are reported in Table 5.5. The OLS estimate of the return to education for females is 11.1 per cent in the specification without labour market experience and 14.3 per cent in the equation with labour market experience. The first is lower than that found for men

[18]The residuals are from the years of education equations which exclude ability. The standard errors in our wage equations are corrected for heteroscedasticity and for the inclusion of generated regressors.

and the second identical to that obtained for men. For women, however, the return to experience is lower than that for men at 5.6 per cent. Therefore the benefit of undertaking an extra year of education, rather than a year of labour market experiences estimated to be around 8.7 per cent in the OLS specification including experience compared to 11.1 per cent in the specification which excludes experience. The results of the IV estimation procedures, however, once again suggest that the returns to education are significantly underestimated by OLS and that schooling is endogenous (and/or measured with error). The corrected estimates are 14.9 per cent for the specification without labour market experience and 16.9 per cent when experience is included, with a return to experience of 5.5 per cent. This latter estimate suggests that the benefit of undertaking an extra year of education rather than a years labour market experience is around 11.4 per cent which is again significantly below the estimate obtained when we do no control for actual labour market experience. For women, unlike men, it appears important to control for actual labour market experience and when we do this our IV estimates of the returns to education for men and women are very similar.

It should be remembered, however, that our years of education variable measures years of full-time education only and is probably a poor measure of true educational outcomes, as mentioned earlier. We therefore, move onto look at the returns to highest qualifications.

The Returns to Highest Qualifications

The estimated returns to individual's highest qualifications by the age of 23 are presented in Table 5.6 for men and in Table 5.7 for women.

The base group in these equations are individuals with no school or post-school qualifications by the age of 23. The OLS estimates presented in the first two columns suggest that there are significant returns to all types of qualifications. It is clear from the table that the estimated returns to experience are considerably lower when we use highest qualifications than when

Table 5.6: Male Returns to Highest Qualifications

Variable	Ordinary Least Squares				Instrumental Variables			
	Coef.	(S.E.)	Coef.	(S.E.)	Coef.	(S.E.)	Coef.	(S.E)
Constant	1.578	(0.036)	1.193	(0.082)	1.438	(0.041)	0.999	(0.083)
Highest Qualification 1981:								
Other	0.130	(0.038)	0.122	(0.037)	0.200	(0.040)	0.195	(0.039)
O Level	0.224	(0.033)	0.218	(0.032)	0.279	(0.033)	0.276	(0.033)
Lower Vocational	0.164	(0.028)	0.153	(0.028)	0.282	(0.033)	0.277	(0.032)
5 + O Levels	0.288	(0.038)	0.298	(0.038)	0.391	(0.040)	0.409	(0.039)
Middle Vocational	0.258	(0.026)	0.257	(0.026)	0.431	(0.037)	0.441	(0.037)
A Levels	0.396	(0.038)	0.455	(0.038)	0.564	(0.046)	0.640	(0.046)
Upper Vocational	0.404	(0.033)	0.427	(0.034)	0.645	(0.048)	0.686	(0.049)
Degree	0.558	(0.028)	0.681	(0.035)	0.843	(0.050)	0.998	(0.055)
Experience			0.024	(0.005)			0.027	(0.005)
$\widehat{\lambda_q}$					-0.115	(0.016)	-0.122	(0.016)
Number of observations	1932		1932		1932		1932	
P-value regional dummies	0.000		0.000		0.000		0.000	
Log Likelihood	-744.24		-731.156		-717.141		-700.35	
R^2	0.2511		0.2611		0.2718		0.2843	

we use years of full-time education. The OLS returns to experience are now estimated to be around 2.4 per cent per year rather than over 7 per cent. These OLS estimates suggest that a man with a degree receives about 70 per cent more in 1991 than a man with no qualifications, and around 22 per cent more than individuals with A levels.

Our IV estimates of the returns to highest qualifications are once again significantly above the corresponding OLS estimates and the selection terms in our wage equations once again suggest that education is endogenous. If we look at our IV estimates when labour market experience is included, we see that a man with a degree gets exactly double that of an unqualified person in 1991 and around 35 per cent more than individuals with A levels. The estimated returns to experience are around 2.7 per cent per year.

The results for females are given in Table 5.7 and again are broadly comparable to those for men. The OLS estimates suggest that a women with a degree gets around 75 per cent more than an unqualified women in 1991, whereas the IV estimate suggests that she gets more than double. Interestingly, the returns to experience for women in this specification are well above those received by men at 4.3 per cent per year. Again it is clear from the ta-

Table 5.7: Female Returns to Highest Qualifications

Variable	Ordinary Least Squares				Instrumental Variables			
	Coef.	(S.E.)	Coef.	(S.E.)	Coef.	(S.E.)	Coef.	(S.E)
Constant	1.176	(0.047)	0.599	(0.057)	1.087	(0.049)	0.527	(0.057)
Highest Qualification 1981:								
Other	0.156	(0.046)	0.088	(0.043)	0.199	(0.045)	0.128	(0.042)
O Level	0.114	(0.029)	0.084	(0.027)	0.179	(0.032)	0.143	(0.029)
Lower Vocational	0.172	(0.042)	0.134	(0.039)	0.268	(0.047)	0.221	(0.043)
5 + O Levels	0.329	(0.034)	0.286	(0.031)	0.431	(0.040)	0.377	(0.037)
Middle Vocational	0.343	(0.039)	0.295	(0.035)	0.464	(0.046)	0.404	(0.042)
A Levels	0.618	(0.043)	0.613	(0.042)	0.720	(0.047)	0.704	(0.046)
Upper Vocational	0.624	(0.035)	0.592	(0.034)	0.790	(0.052)	0.741	(0.050)
Degree	0.755	(0.033)	0.867	(0.031)	0.958	(0.054)	1.047	(0.049)
Experience			0.043	(0.003)			0.043	(0.003)
$\widehat{\lambda}_q$					-0.087	(0.018)	-0.077	(0.017)
Number of observations	1580		1580		1580		1580	
P-value regional dummies	0.000		0.000		0.000		0.000	
Log Likelihood	-691.09		-582.96		-677.74		-570.78	
R^2	0.3741		0.4542		0.3846		0.4625	

ble that highest qualifications appear to be endogenous and estimates which do not take into account this endogeneity significantly underestimate these returns. The corrected estimate of the return to a degree versus A levels is around 40 per cent compared to the OLS estimate of 30 per cent.

5.4.3 Returns to Ability

Including Proxies of Ability

The results we have presented so far have not utilised the results from the ability tests undertaken by our sample at the age of seven. It was clear from our reduced from schooling and qualification equations, that more able people, on average, undertook more years of education and that the probability of undertaking higher qualifications increased with ability. Do more able people have a higher level of earnings, controlling for education? What affect does proxying ability have on our estimates of the returns to education and qualifications?

The results of including proxies of ability for men are given in Tables 5.8 and 5.9. In the first column of these tables we have our OLS estimates from the previous subsection which include experience but exclude ability. In the second column we have the results of our OLS estimates once ability has been included. The third and the fourth columns give the corresponding IV estimates[19].

Table 5.8: Ability, Education and Male Wages

Variable	Ordinary Least Squares				Instrumental Variables			
	Coef.	(S.E.)	Coef.	(S.E.)	Coef.	(S.E.)	Coef.	(S.E)
Constant	-1.020	(0.173)	-0.841	(0.174)	-1.503	(0.190)	-1.198	(0.210)
Years of Education	0.143	(0.007)	0.123	(0.007)	0.186	(0.010)	0.155	(0.013)
Experience	0.071	(0.006)	0.065	(0.006)	0.068	(0.006)	0.065	(0.006)
Maths ability:								
2nd quintile			0.079	(0.028)			0.077	(0.028)
3rd quintile			0.096	(0.029)			0.087	(0.029)
4th quintile			0.115	(0.029)			0.103	(0.029)
5th quintile			0.167	(0.030)			0.137	(0.032)
Verbal ability:								
2nd quintile			0.070	(0.026)			0.054	(0.027)
3rd quintile			0.072	(0.027)			0.047	(0.027)
4th quintile			0.116	(0.027)			0.076	(0.030)
5th quintile			0.118	(0.029)			0.058	(0.033)
Education residuals					-0.065	(0.009)	-0.040	(0.012)
Number of observations	1932		1932		1932		1932	
P-value regional dummies	0.000		0.000		0.000		0.000	
P-value ability dummies			0.000				0.000	
Log Likelihood	-739.90		-697.567		-710.83		-697.567	
R^2	0.2544		0.2789		0.2765		0.2915	

From the second column of Table 5.8 we see that there are significant returns to both arithmetic and verbal ability for men and that by taking this into account our OLS estimates of the returns to education are now 12.3 per cent, some 2 percentage points lower than the OLS estimate obtained in the previous subsection. In our IV specification, there is again significant returns to ability, particularly arithmetic ability, and our IV estimate is now 15.5 per cent compared to 18.6 per cent. Years of education is still clearly endogenous in this specification. In the IV specification, the return to an extra year of education, compared to a years labour market experience is reduced from 11.8 per cent to 9.0 per cent when we include measures of ability.

If we look at the corresponding estimates for our highest qualification specification in Table 5.9 a similar story emerges. In the OLS specification,

[19]For the wage equation which includes proxies of ability, the schooling residuals are taken from the schooling equation which also included these proxies of ability.

Table 5.9: Ability, Highest Qualifications and Male Wages

Variable	Ordinary Least Squares				Instrumental Variables			
	Coef.	(S.E.)	Coef.	(S.E.)	Coef.	(S.E.)	Coef.	(S.E)
Constant	1.193	(0.082)	1.099	(0.082)	0.999	(0.083)	0.995	(0.084)
Highest Qualification 1981:								
Other	0.122	(0.037)	0.096	(0.037)	0.195	(0.039)	0.165	(0.041)
O Level	0.218	(0.032)	0.165	(0.032)	0.276	(0.033)	0.242	(0.037)
Lower Vocational	0.153	(0.028)	0.122	(0.028)	0.277	(0.032)	0.241	(0.039)
5 + O Levels	0.298	(0.038)	0.224	(0.038)	0.409	(0.039)	0.352	(0.047)
Middle Vocational	0.257	(0.026)	0.204	(0.026)	0.441	(0.037)	0.381	(0.049)
A Levels	0.455	(0.038)	0.374	(0.039)	0.640	(0.046)	0.569	(0.061)
Upper Vocational	0.427	(0.034)	0.365	(0.034)	0.686	(0.049)	0.608	(0.065)
Degree	0.681	(0.035)	0.579	(0.037)	0.998	(0.055)	0.891	(0.079)
Experience	0.024	(0.005)	0.024	(0.005)	0.027	(0.005)	0.026	(0.005)
Maths ability:								
2nd quintile			0.067	(0.028)			0.050	(0.028)
3rd quintile			0.068	(0.029)			0.040	(0.030)
4th quintile			0.098	(0.029)			0.067	(0.029)
5th quintile			0.139	(0.030)			0.084	(0.033)
Verbal ability:								
2nd quintile			0.065	(0.026)			0.033	(0.027)
3rd quintile			0.056	(0.027)			0.003	(0.029)
4th quintile			0.095	(0.028)			0.022	(0.033)
5th quintile			0.115	(0.029)			0.033	(0.034)
$\widehat{\lambda_q}$					-0.122	(0.016)	-0.098	(0.022)
Number of observations	1932		1932		1932		1932	
P-value regional dummies	0.000		0.000		0.000		0.000	
P-value ability dummies			0.000				0.2042	
Log Likelihood	-731.16		-701.65		-700.35		-690.77	
R^2	0.2611		0.2834		0.2843		0.2914	

our ability variables are again positive and significant, and result in a downward revision of our estimated returns to various qualifications. For instance the returns to degrees versus no qualifications is now only around 58 per cent compared with our OLS estimate of 68 per cent when we did not include measures of ability. When we correct for the endogeneity of these qualifications, our estimates of the returns to qualifications rise, but these IV estimates are still significantly lower than the corresponding IV estimates when we did not include ability. Now the estimated return to a degree versus no qualifications is around 89 per cent compared to an estimated return of 100 per cent when we do no include measures of ability. Interestingly, our ability measures are no longer jointly significant in this specification, though it is clear that men who were in the top 40 per cent of those taking the arithmetic ability test at the age of seven do significantly better than those who were not.

The results suggest that there are significant returns to ability and that estimates of the returns to education which do not take this into account overestimate the returns to education and qualifications. They also suggest that even once account is taken of ability, there still remains unobserved individual effects which are correlated with educational outcomes and estimates which do not take this into account underestimate the true returns to education. The upward bias caused by not taking into account unobserved ability is smaller than the downward bias caused by not taking into account other correlated individual effects, and the fully corrected estimates are above OLS estimates which do not take into account unobserved ability and correlated individual effects.

The corresponding results for women are given in Tables 5.10 and 5.11. For women, there are also clear returns to ability, particularly verbal ability. This once again results in a downward revision of our OLS estimates of the returns to education. From the fourth column of Table 5.10, it again appears that when account is also taken of other unobserved individual effects which are correlated with education, our corrected estimates are higher than those which do not take this into account, but in this specification the test of exogeneity of years of education is accepted.

Table 5.10: Ability, Education and Female Wages

Variable	Ordinary Least Squares				Instrumental Variables			
	Coef.	(S.E.)	Coef.	(S.E.)	Coef.	(S.E.)	Coef.	(S.E)
Constant	-1.040	(0.089)	-1.049	(0.093)	-1.347	(0.118)	-1.186	(0.139)
Years of Education	0.143	(0.005)	0.133	(0.005)	0.169	(0.009)	0.145	(0.011)
Experience	0.056	(0.003)	0.055	(0.003)	0.055	(0.003)	0.054	(0.003)
Maths ability:								
2nd quintile			0.049	(0.030)			0.047	(0.029)
3rd quintile			0.110	(0.030)			0.105	(0.030)
4th quintile			0.072	(0.030)			0.065	(0.030)
5th quintile			0.076	(0.032)			0.066	(0.033)
Verbal ability:								
2nd quintile			0.068	(0.034)			0.066	(0.035)
3rd quintile			0.087	(0.034)			0.082	(0.034)
4th quintile			0.120	(0.034)			0.107	(0.036)
5th quintile			0.147	(0.036)			0.127	(0.039)
Education residuals					-0.040	(0.010)	-0.017	(0.012)
Number of observations	1580		1580		1580		1580	
P-value regional dummies	0.000		0.000		0.000		0.000	
P-value ability dummies			0.000				0.000	
Log Likelihood	-638.18		-617.14		-629.60		-615.96	
R^2	0.4146		0.4300		0.4210		0.4309	

If we look at the highest qualification estimates, the impact of including the ability measures is less pronounced than for men, but again slightly reduces our estimates of the returns to qualifications. In our IV specification, our ability measures are no longer jointly significant, though our education measure still appears to be endogenous. Once again it would seem that the upward bias associated with not including ability in our wage equations is more than outweighed by the downward bias caused by ignoring other correlated individual effects.

Do the returns to education and qualification vary by ability?

The results of the last subsection suggest that more able people may have higher levels of earnings. The question we now move on to consider, is whether more able individuals have higher returns to education or qualifications. Also we want to determine whether returns to experience vary by ability.

Table 5.11: Ability, Highest Qualifications and Female Wages

Variable	Ordinary Least Squares				Instrumental Variables			
	Coef.	(S.E.)	Coef.	(S.E.)	Coef.	(S.E.)	Coef.	(S.E)
Constant	0.599	(0.057)	0.518	(0.062)	0.527	(0.057)	0.491	(0.061)
Highest Qualification 1981:								
Other	0.088	(0.043)	0.083	(0.043)	0.128	(0.042)	0.123	(0.045)
O Level	0.084	(0.027)	0.055	(0.028)	0.143	(0.029)	0.123	(0.037)
Lower Vocational	0.134	(0.039)	0.105	(0.041)	0.221	(0.043)	0.197	(0.052)
5 + O Levels	0.286	(0.031)	0.246	(0.032)	0.377	(0.037)	0.352	(0.049)
Middle Vocational	0.295	(0.035)	0.254	(0.037)	0.404	(0.042)	0.373	(0.056)
A Levels	0.613	(0.042)	0.558	(0.045)	0.704	(0.046)	0.673	(0.060)
Upper Vocational	0.592	(0.034)	0.555	(0.036)	0.741	(0.050)	0.708	(0.069)
Degree	0.867	(0.031)	0.814	(0.035)	1.047	(0.049)	1.008	(0.075)
Experience	0.043	(0.003)	0.043	(0.003)	0.043	(0.003)	0.043	(0.003)
Maths ability:								
2nd quintile			0.042	(0.028)			0.032	(0.028)
3rd quintile			0.070	(0.030)			0.048	(0.031)
4th quintile			0.057	(0.029)			0.035	(0.030)
5th quintile			0.036	(0.032)			0.005	(0.033)
Verbal ability:								
2nd quintile			0.055	(0.033)			0.037	(0.034)
3rd quintile			0.073	(0.034)			0.039	(0.036)
4th quintile			0.086	(0.035)			0.030	(0.040)
5th quintile			0.109	(0.036)			0.042	(0.043)
$\widehat{\lambda}_q$					-0.077	(0.017)	-0.066	(0.023)
Number of observations	1580		1580		1580		1580	
P-value regional dummies	0.000		0.000		0.000		0.000	
P-value ability dummies			0.017				0.7017	
Log Likelihood	-582.96		-573.70		-570.78		-568.26	
R^2	0.4542		0.4605		0.4625		0.4642	

Table 5.12: Heterogeneity in Male Returns to Education

Variable	Low Ability		Middle Ability		High Ability		P-value for F test of equality
	Coef.	(S.E.)	Coef.	(S.E.)	Coef.	(S.E.)	
Years of Education	0.167	(0.015)	0.160	(0.013)	0.157	(0.013)	0.425
Experience	0.058	(0.007)	0.065	(0.006)	0.077	(0.007)	0.001
Number of observations	1932						
P-value regional dummies	0.000						
P-value ability dummies	0.020						
Log Likelihood	-680.38						
R^2	0.2990						

To look at this question we take our IV specifications from the previous section which included measures of ability and divide our sample of men and women into high, middle and low ability groups. We define an individual to be of high ability if they were in the top two quintiles in both of the ability tests (which covers around 21 per cent of men and 15 per cent of women) and to be of low ability if they were in the bottom two quintiles in both ability tests (which covers 27 per cent of men and 30 per cent of women). All other individuals are defined to be of middle ability. We then look to see whether the returns to years of education and experience vary for these different ability groups by estimating a model like that given by equation (5.17). In Table 5.12 we have the results for our years of education specification. This suggests that the returns to education do not vary across ability groups. It does, however, appear that returns to experience with vary by ability group, with more able men receiving a higher return to labour market experience.

Table 5.13: Heterogeneity in Male Returns to Qualifications

Variable	Low Ability		Middle Ability		High Ability		P-value for F test
	Coef.	(S.E.)	Coef.	(S.E.)	Coef.	(S.E.)	of equality
Highest Qualification 1981:							
None			0.025	(0.192)	0.138	(0.240)	0.816
Other	0.279	(0.070)	0.143	(0.197)	0.229	(0.257)	0.789
O Level	0.185	(0.074)	0.289	(0.197)	0.293	(0.239)	0.881
Lowest Vocational	0.334	(0.060)	0.237	(0.197)	0.281	(0.241)	0.890
5 + O Levels	0.399	(0.099)	0.365	(0.196)	0.394	(0.237)	0.982
Middle Vocational	0.405	(0.067)	0.410	(0.198)	0.414	(0.235)	0.999
A Levels	0.651	(0.116)	0.548	(0.196)	0.652	(0.222)	0.769
Highest Vocational	0.597	(0.103)	0.651	(0.199)	0.632	(0.231)	0.965
Degree	0.914	(0.122)	0.925	(0.193)	0.936	(0.210)	0.993
Experience	0.022	(0.010)	0.024	(0.006)	0.031	(0.010)	0.769
Number of observations	1932						
P-value regional dummies	0.000						
P-value ability dummies	0.2349						
Log Likelihood	-677.29						
R^2	0.3012						

In Table 5.13, however, when we consider returns to different qualifications rather than years of education, there is no evidence that either the returns to qualifications or to labour market experience vary by ability groups.

Table 5.14: Heterogeneity in Female Returns to Education

Variable	Low Ability Coef.	(S.E.)	Middle Ability Coef.	(S.E.)	High Ability Coef.	(S.E.)	P-value for F test of equality
Years of Education	0.164	(0.013)	0.149	(0.012)	0.141	(0.011)	0.030
Experience	0.048	(0.005)	0.055	(0.003)	0.059	(0.005)	0.284
Number of observations	1580						
P-value regional dummies	0.000						
P-value ability dummies	0.001						
Log Likelihood	-612.26						
R^2	0.4335						

The corresponding results for women are given in Tables 5.14 and 5.15. From Table 5.14 we see that there is some evidence that the returns to years of education increase with ability. This does no appear to carry through to the returns to experience. If we focus on returns to highest qualifications we see that from Table 5.15 that there appears to be some variability in the returns to lower, middle and higher vocational qualifications, however, the returns appear largest for low ability people.

Table 5.15: Heterogeneity in Female Returns to Qualifications

Variable	Low Ability Coef.	(S.E.)	Middle Ability Coef.	(S.E.)	High Ability Coef.	(S.E.)	P-value for F test of equality
Highest Qualification 1981:							
None			-0.137	(0.089)	-0.328	(0.147)	0.074
Other	0.166	(0.095)	-0.016	(0.103)	-0.253	(0.169)	0.097
O Level	0.068	(0.075)	-0.034	(0.095)	-0.115	(0.143)	0.494
Lowest Vocational	0.306	(0.103)	0.048	(0.105)	-0.196	(0.162)	0.021
5 + O Levels	0.229	(0.082)	0.211	(0.104)	0.070	(0.151)	0.517
Middle Vocational	0.501	(0.093)	0.238	(0.108)	0.027	(0.158)	0.018
A Levels	0.263	(0.159)	0.492	(0.111)	0.431	(0.161)	0.425
Highest Vocational	0.838	(0.104)	0.559	(0.121)	0.383	(0.154)	0.020
Degree	1.054	(0.229)	0.831	(0.116)	0.745	(0.147)	0.425
Experience	0.037	(0.005)	0.043	(0.003)	0.048	(0.007)	0.453
Number of observations	1580						
P-value regional dummies	0.000						
P-value ability dummies	0.2516						
Log Likelihood	-556.00						
R^2	0.4725						

The results of this section suggest that there is only very weak evidence that the returns to education and qualifications vary for individuals with different abilities. It would appear that ability has a bigger impact on the level of earnings, and when this is taken into account, the estimated returns to education and qualifications are reduced for all individuals, regardless of ability.

Is there a measurement error problem?

In looking at the measurement error problem we focus on our highest qualification specifications. We now treat the results of our ability tests as endogenous and construct selection terms for our maths and verbal ability tests from ordered probits carried out on these test results. The ability ordered probits are reported in Table 5.21 in Appendix A.5.4. Our identifying assumptions for our ability measures include teacher's assessment of the child's reading and numeric ability at the age of seven. For men, there appears that there is no significant measurement error problem associated with using our proxies of ability. Both of the ability selection terms are insignificant in Table 5.16. For women, there appears that there may be a measurement error problem with our measure of arithmetic ability, though all selection terms are fairly imprecisely determined.[20].

5.4.4 How Robust are our IV estimates?

In all the IV estimation that we have carried out so far, we have only included education, region, ability and experience variables as explanatory variables in our wage equations. However, studies like Bound, Jaeger and Baker [39] show that poor instrument selection can create more problems than it solves. A relatively weak correlation between potential instruments and wages, can result in a large upward bias in IV estimates. Instruments firstly need to be significant in the reduced form education equations. Secondly, they should have no legitimate role in a wage equation, controlling for education.

We have a large set of instruments which are both individually and jointly significant in our reduced form education equations presented in Tables 5.2

[20]If we exclude the mills ratio from the highest qualification probit this is still true.

Table 5.16: Ability, Measurement Error and the Returns to Qualifications

Variable	Males				Females			
	Coef.	(S.E.)	Coef.	(S.E.)	Coef.	(S.E.)	Coef.	(S.E)
Constant	0.995	(0.084)	0.991	(0.085)	0.491	(0.061)	0.444	(0.064)
Highest Qualification 1981:								
Other	0.165	(0.041)	0.141	(0.043)	0.123	(0.045)	0.103	(0.046)
O Level	0.242	(0.037)	0.205	(0.040)	0.123	(0.037)	0.080	(0.046)
Lower Vocational	0.241	(0.039)	0.192	(0.047)	0.197	(0.052)	0.150	(0.062)
5 + O Levels	0.352	(0.047)	0.296	(0.056)	0.352	(0.049)	0.283	(0.064)
Middle Vocational	0.381	(0.049)	0.313	(0.061)	0.373	(0.056)	0.301	(0.073)
A Levels	0.569	(0.061)	0.485	(0.076)	0.673	(0.060)	0.595	(0.079)
Upper Vocational	0.608	(0.065)	0.515	(0.082)	0.708	(0.069)	0.618	(0.092)
Degree	0.891	(0.079)	0.770	(0.104)	1.008	(0.075)	0.892	(0.107)
Experience	0.026	(0.005)	0.026	(0.005)	0.043	(0.003)	0.043	(0.003)
Maths ability:								
2nd quintile	0.050	(0.028)	0.077	(0.035)	0.032	(0.028)	0.102	(0.038)
3rd quintile	0.040	(0.030)	0.083	(0.045)	0.048	(0.031)	0.160	(0.049)
4th quintile	0.067	(0.029)	0.116	(0.054)	0.035	(0.030)	0.179	(0.063)
5th quintile	0.084	(0.033)	0.166	(0.074)	0.005	(0.033)	0.220	(0.085)
Verbal ability:								
2nd quintile	0.033	(0.027)	0.053	(0.033)	0.037	(0.034)	0.033	(0.041)
3rd quintile	0.003	(0.029)	0.026	(0.040)	0.039	(0.036)	0.029	(0.050)
4th quintile	0.022	(0.033)	0.060	(0.052)	0.030	(0.040)	0.022	(0.063)
5th quintile	0.033	(0.034)	0.077	(0.067)	0.042	(0.043)	0.023	(0.090)
$\widehat{\lambda}_q$	-0.098	(0.022)	-0.066	(0.028)	-0.066	(0.023)	-0.036	(0.032)
$\widehat{\lambda}_{ma}$			-0.020	(0.022)			-0.069	(0.027)
$\widehat{\lambda}_{va}$			-0.008	(0.018)			0.008	(0.024)
Number of observations	1932		1932		1580		1580	
P-value regional dummies	0.000		0.000		0.000		0.000	
P-value ability dummies	0.2042		0.1350		0.7017		0.090	
Log Likelihood	-690.77		-689.04		-568.26		-563.11	
R^2	0.2914		0.2927		0.4642		0.4677	

and5.3. The second requirement is of course untestable, though we can test for the validity of over-identifying restrictions using a Sargan test. Our instruments generally pass such tests. In Table 5.17 we expand our explanatory variables in our wage equations to include parent's education and social class variables, whether the family was experiencing financial difficulties in 1974, as well as the number of siblings and number of older siblings the individual has. Our identifying restrictions are now based on parental interest variables, whether the individual had brothers or sisters only, and the teacher's rating of the child's ability at the age of seven. In the first column we report our previous IV results and in the second column we report the IV results when we include these extra regressors in our wage equations. As can be seen from the table, our IV estimates are very similar in both specifications. A joint test of the significance of these extra regressors are however, accepted in the male equation, though are rejected in the female equation at conventional levels.

5.5 Education and Gender Wage Differentials

In this section we look at the observed gender wage differential for our sample and look at how this varies across qualification groups. We also decompose these wage differentials into differences that can be explained in terms of observed average differences in the characteristics of men and women and that attributable to women's characteristics being valued differently to those of men. The results of doing this are given in Table 6.12. The estimates are based on our IV highest qualification equations which include ability reported in the first column of the previous Table (and earlier).

The results from this Table show that less than one-third of the observed wage differential between men and women is attributable to differences in observed characteristics such as labour market experience, education and regional location. It would appear that there are substantial pay differences

Table 5.17: Robustness of IV estimates of the Returns to Qualifications

Variable	Males				Females			
	Coef.	(S.E.)	Coef.	(S.E.)	Coef.	(S.E.)	Coef.	(S.E)
Constant	0.995	(0.084)	1.107	(0.121)	0.491	(0.061)	0.528	(0.115)
Highest Qualification 1981:								
Other	0.165	(0.041)	0.172	(0.046)	0.123	(0.045)	0.133	(0.051)
O Level	0.242	(0.037)	0.244	(0.046)	0.123	(0.037)	0.143	(0.048)
Lower Vocational	0.241	(0.039)	0.247	(0.053)	0.197	(0.052)	0.227	(0.070)
5 + O Levels	0.352	(0.047)	0.356	(0.062)	0.352	(0.049)	0.381	(0.072)
Middle Vocational	0.381	(0.049)	0.396	(0.074)	0.373	(0.056)	0.412	(0.080)
A Levels	0.569	(0.061)	0.589	(0.089)	0.673	(0.060)	0.711	(0.089)
Upper Vocational	0.608	(0.065)	0.627	(0.100)	0.708	(0.069)	0.755	(0.100)
Degree	0.891	(0.079)	0.920	(0.125)	1.008	(0.075)	1.074	(0.129)
Experience	0.026	(0.005)	0.027	(0.005)	0.043	(0.003)	0.042	(0.003)
Father's years of education			0.008	(0.007)			-0.002	(0.008)
No Father Figure			0.032	(0.080)			-0.009	(0.086)
Mother's years of education			-0.017	(0.008)			-0.006	(0.009)
No Mother Figure			-0.213	(0.091)			-0.026	(0.119)
Father's social class 1974:								
Prof/Intermediate			-0.063	(0.044)			0.058	(0.042)
Skilled non-manual			-0.048	(0.048)			0.003	(0.045)
Skilled manual			-0.087	(0.039)			0.021	(0.038)
Semi-skilled			-0.101	(0.042)			0.013	(0.044)
Unskilled			-0.117	(0.057)			-0.013	(0.054)
Mother's social class 1974:								
Prof/Intermediate			0.043	(0.030)			-0.031	(0.036)
Skilled non-manual			0.054	(0.022)			0.005	(0.026)
Skilled manual			0.088	(0.042)			0.024	(0.044)
Semi-skilled			0.011	(0.023)			0.022	(0.025)
Unskilled			0.020	(0.033)			0.053	(0.030)
Financial Difficulties 1974			-0.018	(0.029)			-0.004	(0.031)
Number of siblings			0.011	(0.007)			-0.002	(0.008)
Number of older siblings			-0.005	(0.008)			0.011	(0.010)
$\widehat{\lambda}_q$	-0.098	(0.022)	-0.105	(0.035)	-0.066	(0.023)	-0.084	(0.035)
Number of observations	1932		1932		1580		1580	
P-value regional dummies	0.000		0.000		0.000		0.000	
P-value ability dummies	0.2042		0.3840		0.7017		0.6862	
P-value Background Variables			0.034				0.7247	
Log Likelihood	-690.77		-676.95		-568.26		-562.44	
R^2	0.2914		0.3015		0.4642		0.4681	

Table 5.18: Gender Wage Differentials by Education Qualification

Highest Qualification	$(\overline{x}_m - \overline{x}_f)'\widehat{\beta}_m$		$\overline{x}'_f(\widehat{\beta}_m - \widehat{\beta}_f)$		$\widehat{g}$	
	Estimate	(S.E.)	Estimate	(S.E.)	Estimate	(S.E.)
None	0.093	(0.016)	0.240	(0.046)	0.333	(0.042)
Other	0.060	(0.011)	0.270	(0.055)	0.330	(0.054)
O Level	0.084	(0.013)	0.353	(0.041)	0.437	(0.037)
Lowest Vocational	0.070	(0.015)	0.277	(0.045)	0.348	(0.041)
5 + O Levels	0.049	(0.010)	0.243	(0.043)	0.292	(0.041)
Middle Vocational	0.042	(0.012)	0.246	(0.038)	0.288	(0.037)
A Levels	0.035	(0.007)	0.145	(0.050)	0.180	((0.050)
Highest Vocational	0.048	(0.008)	0.140	(0.052)	0.187	(0.052)
Degree	0.016	(0.005)	0.202	((0.053)	0.217	((0.053)
All	0.092	(0.013)	0.245	(0.017)	0.337	(0.012)

that exist for men and women with the same measured skills. This is particularly true for women with degrees where almost all of the observed differential can be attributed to this rather than differences in experience and regional location. This finding is very different to that found in our Australian sample for Degree holders. The biggest gender differentials are found for low skilled workers, particularly for women whose highest qualification by 1981 was O Levels. The results of the Table suggest that observed wage differentials tend to decline with increased education, but even after controlling for observed characteristics, these differences are never eliminated.

One important measured characteristic, which has been ignored in this Chapter, is work related training. By ignoring things like work related training we could be underestimating the importance of differences in observed characteristics to observed wage differentials for men and women. We look at this issue in more detail in the next Chapter.

5.6 Conclusion

If differences in ability are the key determinants of schooling decisions, then estimates of the returns to schooling which do not take this into account will overestimate the returns to such schooling. If differences in discount rates (determined by "access to funds" or "tastes for education") are the most important determinants, then the opposite is true.

We began the Chapter by ignoring ability, and used instrumental variable techniques. The instrumental variables we used to explain variations in educational outcomes were generally variables which measured things like access to funds (for example, whether the family was in serious financial trouble in 1974) and tastes for education (for instance, the interest shown by parents in their child's education at the age of seven). Other instruments also include family composition variables such as birth order and the sex composition of the individual's siblings. We find that the children of parents who showed a lot of interest in their child's education at the age of seven had significantly better education outcomes than children whose parents showed little or no interest. We also argue that these parental interest variables, have no role in a wage equation controlling for education and can therefore be used as instruments for education. Our IV estimates of the returns to education suggest that OLS estimates which do not take into account these other correlated individual effects significantly underestimated the returns to education. This finding could be due to measurement error in our education variables and/or correlated unobserved effects.

The next part of the Chapter concentrated on omitted ability bias. The results we obtained suggest that our proxies of ability are important determinants of both education and the level of earnings received by individuals and that conventional estimates of the returns to education which do not control for this, over-estimate the returns to education. However, when we take into account the effects of *both* omitted ability and other correlated individual effects, the estimated returns to education were still above OLS estimates, though (marginally) below IV estimates which did not include measures of ability.

We also looked at whether the returns to education vary by ability groups. We found very little evidence that this was the case for our sample. We also looked at the issue of measurement error in our proxies of ability, but this did not seem to be important for the results obtained in this Chapter.

Finally, we looked at how the observed wage differences between men and women varied across different education groups. The biggest gender differentials were found to exist for low skilled workers, particularly for women whose highest qualification by 1981 was O Levels. The results of our work suggest that observed wage differentials tend to decline with increased education, but even after controlling for observed characteristics, these differences are never eliminated.

In all the empirical work we have looked at so far we have only looked at the impact of formal education. But as suggested standard human capital models such as the Ben-Porath model discussed in Chapter 2, on-the-job training and other work related training is important. These model also suggest that on-the-job training and education are complements, therefore if they are positively correlated, we could be attributing effects to education which are in fact due to on-the-job training. This issue is explored in more detail in the next Chapter.

Appendices

A.5.1 Summary Statistics

Table 5.19: Summary Statistics

Variable	Males		Females	
	1932 Observations		1580 Observeations	
	Mean	(Std Dev.)	Mean	(Std Dev.)
Real log hourly wage	1.626	(0.411)	1.289	(0.474)
Years of Education	12.251	(2.055)	12.300	(2.027)
Highest Qualification 1981:				
None	0.172	(0.377)	0.221	(0.415)
Other	0.048	(0.214)	0.037	(0.188)
O Level	0.104	(0.305)	0.208	(0.406)
Lower Vocational	0.102	(0.303)	0.062	(0.241)
5 + O Levels	0.079	(0.269)	0.115	(0.319)
Middle Vocational	0.188	(0.391)	0.058	(0.233)
A Levels	0.076	(0.264)	0.061	(0.239)
Upper Vocational	0.100	(0.300)	0.123	(0.329)
Degree	0.132	(0.339)	0.116	(0.320)
Experience	15.414	(2.500)	13.290	(3.317)
Maths ability:				
1st quintile	0.151	(0.358)	0.168	(0.374)
2nd quintile	0.185	(0.388)	0.202	(0.402)
3rd quintile	0.205	(0.404)	0.201	(0.401)
4th quintile	0.217	(0.412)	0.222	(0.416)
5th quintile	0.242	(0.429)	0.208	(0.406)
Verbal ability:				
1st quintile	0.168	(0.374)	0.099	(0.298)
2nd quintile	0.207	(0.405)	0.165	(0.371)
3rd quintile	0.220	(0.414)	0.206	(0.405)
4th quintile	0.216	(0.412)	0.260	(0.439)
5th quintile	0.190	(0.392)	0.270	(0.444)
Low ability	0.210	(0.408)	0.156	(0.363)
Middle ability	0.523	(0.500)	0.547	(0.498)
High ability	0.267	(0.442)	0.297	(0.457)
Teacher's rating:				
Avid reader	0.054	(0.227)	0.087	(0.282)
Above average reader	0.248	(0.432)	0.326	(0.469)
Average reader	0.456	(0.498)	0.469	(0.499)
Excellent number skills	0.048	(0.214)	0.030	(0.170)
Good number skills	0.231	(0.422)	0.194	(0.396)
Average number skills	0.440	(0.497)	0.492	(0.500)
Father's interest in edn:				
Very interested	0.313	(0.464)	0.301	(0.459)
Some interest	0.246	(0.431)	0.210	(0.408)
Mother's interest in edn:				
Very interested	0.434	(0.496)	0.472	(0.499)
Some interest	0.383	(0.486)	0.374	(0.484)
Father's years of education	9.517	(2.887)	9.309	(3.117)
No Father Figure	0.050	(0.217)	0.069	(0.254)
Mother's years of education	9.869	(1.903)	9.864	(1.998)
No Mother Figure	0.012	(0.111)	0.016	(0.125)
Father's social class 1974:				
Prof/Intermediate	0.250	(0.433)	0.239	(0.426)
Skilled non-manual	0.101	(0.301)	0.094	(0.292)
Skilled manual	0.389	(0.488)	0.389	(0.488)
Semi-skilled	0.129	(0.335)	0.115	(0.319)
Unskilled	0.026	(0.160)	0.035	(0.185)
Mother's social class 1974:				
Prof/Intermediate	0.122	(0.328)	0.122	(0.327)
Skilled non-manual	0.236	(0.424)	0.227	(0.419)
Skilled manual	0.043	(0.203)	0.054	(0.227)
Semi-skilled	0.212	(0.409)	0.223	(0.416)
Unskilled	0.074	(0.262)	0.069	(0.254)
Financial Difficulties 1974	0.107	(0.309)	0.119	(0.324)
Number of siblings	2.163	(1.663)	2.197	(1.674)
Number of older siblings	1.066	(1.331)	1.061	(1.276)
Brothers only	0.268	(0.443)	0.256	(0.437)
Sisters only	0.248	(0.432)	0.244	(0.429)

A.5.2 The Determinants of Education Outcomes

Table 5.20: Determinants of Education Outcomes

Variable	Years of Full-time Education				Highest Qualification			
	Coef.	(S.E.)	Coef.	(S.E.)	Coef.	(S.E.)	Coef.	(S.E)
Constant	8.143	(0.299)	8.088	(0.303)				
Maths ability:								
2nd quintile			0.054	(0.100)			0.129	(0.063)
3rd quintile			0.114	(0.103)			0.233	(0.065)
4th quintile			0.197	(0.107)			0.180	(0.067)
5th quintile			0.400	(0.115)			0.338	(0.071)
Verbal ability:								
2nd quintile			0.143	(0.111)			0.182	(0.071)
3rd quintile			0.171	(0.122)			0.234	(0.077)
4th quintile			0.409	(0.128)			0.396	(0.080)
5th quintile			0.673	(0.138)			0.431	(0.086)
Teacher's rating:								
Avid reader	1.316	(0.155)	0.835	(0.174)	0.949	(0.097)	0.642	(0.109)
Above average reader	0.817	(0.111)	0.432	(0.132)	0.689	(0.069)	0.413	(0.082)
Average reader	0.295	(0.092)	0.127	(0.105)	0.389	(0.058)	0.223	(0.066)
Excellent number skills	0.625	(0.172)	0.353	(0.179)	0.615	(0.107)	0.434	(0.112)
Good number skills	0.304	(0.102)	0.102	(0.109)	0.504	(0.062)	0.372	(0.067)
Average number skills	0.136	(0.080)	0.026	(0.083)	0.326	(0.049)	0.244	(0.052)
Father's interest in edn:								
Very interested	0.199	(0.091)	0.166	(0.090)	0.180	(0.056)	0.162	(0.056)
Some interest	0.161	(0.080)	0.147	(0.080)	0.045	(0.049)	0.032	(0.049)
Mother's interest in edn:								
Very interested	0.322	(0.106)	0.313	(0.105)	0.184	(0.065)	0.176	(0.066)
Some interest	0.015	(0.092)	0.015	(0.092)	0.161	(0.058)	0.163	(0.058)
Father's years of education	0.113	(0.020)	0.107	(0.020)	0.068	(0.013)	0.064	(0.013)
No Father Figure	1.071	(0.258)	1.013	(0.257)	0.682	(0.161)	0.637	(0.162)
Mother's years of education	0.246	(0.024)	0.242	(0.024)	0.095	(0.015)	0.095	(0.015)
No Mother Figure	2.047	(0.343)	1.985	(0.341)				
Father's social class 1974:					0.897	(0.213)	0.864	(0.214)
Prof/Intermediate	0.584	(0.148)	0.553	(0.147)	0.368	(0.092)	0.334	(0.093)
Skilled non-manual	0.201	(0.160)	0.191	(0.159)	0.219	(0.100)	0.202	(0.100)
Skilled manual	-0.104	(0.136)	-0.093	(0.136)	0.077	(0.085)	0.073	(0.086)
Semi-skilled	-0.172	(0.152)	-0.166	(0.151)	-0.054	(0.096)	-0.065	(0.096)
Unskilled	-0.206	(0.207)	-0.214	(0.206)				
Mother's social class 1974:					-0.200	(0.132)	-0.214	(0.133)
Prof/Intermediate	0.134	(0.104)	0.134	(0.103)	0.061	(0.065)	0.062	(0.065)
Skilled non-manual	-0.047	(0.083)	-0.081	(0.083)	-0.019	(0.051)	-0.043	(0.051)
Skilled manual	-0.309	(0.144)	-0.314	(0.143)	-0.070	(0.088)	-0.071	(0.088)
Semi-skilled	-0.213	(0.084)	-0.216	(0.084)	-0.052	(0.052)	-0.057	(0.052)
Unskilled	-0.184	(0.123)	-0.191	(0.122)	-0.046	(0.076)	-0.050	(0.076)
Financial Difficulties 1974	-0.172	(0.107)	-0.150	(0.106)	-0.225	(0.067)	-0.211	(0.067)
Number of siblings	-0.077	(0.027)	-0.067	(0.027)	-0.071	(0.017)	-0.065	(0.017)
Number of older siblings	0.024	(0.031)	0.013	(0.031)	0.016	(0.020)	0.008	(0.020)
Brothers only	0.035	(0.074)	0.050	(0.074)	0.060	(0.046)	0.066	(0.046)
Sisters only	-0.033	(0.076)	-0.040	(0.076)	0.046	(0.047)	0.041	(0.047)
Male	0.035	(0.060)	0.047	(0.060)	0.289	(0.037)	0.294	(0.038)
μ_1					1.628	(0.192)	1.769	(0.197)
μ_2					1.816	(0.193)	1.960	(0.197)
μ_3					2.357	(0.193)	2.506	(0.198)
μ_4					2.624	(0.194)	2.776	(0.198)
μ_5					2.920	(0.194)	3.075	(0.199)
μ_6					3.347	(0.196)	3.506	(0.200)
μ_7					3.601	(0.196)	3.761	(0.201)
μ_8					4.121	(0.198)	4.288	(0.203)
Number of observations	3512		3512		3512		3512	
P-value regional dummies	0.049		0.097		0.007		0.021	
Log Likelihood	-6840.44		-6809.43		-6750.60		-6715.82	
(Pseudo) R^2	0.3096		0.3217		0.0942		0.0989	

A.5.3 Ability Ordered Probits

Table 5.21: Ability Ordered Probits

Variable	Maths Ability				Verbal Ability			
	Males		Females		Males		Females	
	Coef.	(S.E.)	Coef.	(S.E.)	Coef.	(S.E.)	Coef.	(S.E)
Teacher's rating:								
Avid reader	0.643	(0.143)	0.518	(0.148)	2.932	(0.155)	3.198	(0.172)
Above average reader	0.574	(0.092)	0.509	(0.113)	2.434	(0.102)	2.494	(0.125)
Average reader	0.322	(0.074)	0.338	(0.099)	1.348	(0.080)	1.419	(0.105)
Excellent number skills	2.185	(0.161)	1.888	(0.203)	0.411	(0.142)	0.225	(0.203)
Good number skills	1.495	(0.090)	1.364	(0.098)	0.334	(0.088)	0.309	(0.098)
Average number skills	0.864	(0.071)	0.721	(0.073)	0.258	(0.071)	0.146	(0.073)
Father's interest in edn:								
Very interested	0.115	(0.080)	0.041	(0.084)	0.143	(0.080)	0.159	(0.087)
Some interest	0.150	(0.068)	0.130	(0.076)	0.021	(0.069)	0.005	(0.077)
Mother's interest in edn:								
Very interested	0.003	(0.090)	0.221	(0.101)	0.063	(0.091)	0.014	(0.103)
Some interest	0.004	(0.077)	-0.021	(0.090)	0.031	(0.079)	0.023	(0.091)
Father's years of education	-0.001	(0.018)	0.040	(0.019)	0.012	(0.018)	0.036	(0.020)
No Father Figure	-0.022	(0.226)	0.683	(0.243)	0.015	(0.229)	0.319	(0.249)
Mother's years of education	0.042	(0.021)	-0.007	(0.022)	0.026	(0.021)	0.001	(0.023)
No Mother Figure	0.920	(0.319)	-0.031	(0.307)	0.387	(0.312)	-0.020	(0.317)
Father's social class 1974:								
Prof/Intermediate	0.291	(0.128)	0.134	(0.139)	0.132	(0.132)	0.196	(0.142)
Skilled non-manual	0.150	(0.138)	0.023	(0.152)	0.039	(0.141)	0.172	(0.155)
Skilled manual	0.122	(0.118)	-0.002	(0.128)	-0.096	(0.122)	0.026	(0.130)
Semi-skilled	0.092	(0.131)	0.036	(0.144)	-0.003	(0.135)	-0.004	(0.146)
Unskilled	0.002	(0.186)	0.179	(0.185)	-0.071	(0.192)	0.126	(0.189)
Mother's social class 1974:								
Prof/Intermediate	0.124	(0.089)	0.012	(0.099)	-0.143	(0.090)	0.086	(0.103)
Skilled non-manual	0.147	(0.071)	0.083	(0.080)	0.085	(0.072)	0.153	(0.082)
Skilled manual	0.156	(0.130)	0.024	(0.128)	-0.222	(0.132)	0.101	(0.131)
Semi-skilled	0.114	(0.072)	0.026	(0.079)	-0.039	(0.073)	-0.093	(0.081)
Unskilled	0.221	(0.104)	0.109	(0.117)	-0.129	(0.106)	0.009	(0.120)
Financial Difficulties 1974	-0.117	(0.093)	-0.106	(0.099)	-0.037	(0.096)	-0.105	(0.100)
Number of siblings	0.006	(0.024)	-0.005	(0.024)	-0.065	(0.025)	-0.064	(0.025)
Number of older siblings	0.071	(0.027)	0.049	(0.029)	0.019	(0.028)	0.045	(0.030)
Brothers only	-0.078	(0.064)	-0.020	(0.070)	-0.092	(0.064)	0.020	(0.072)
Sisters only	0.001	(0.066)	0.053	(0.071)	0.051	(0.067)	0.050	(0.074)
μ_1	0.593	(0.253)	0.405	(0.297)	0.398	(0.256)	0.420	(0.307)
μ_2	1.396	(0.254)	1.177	(0.298)	1.463	(0.258)	1.439	(0.309)
μ_3	2.094	(0.256)	1.809	(0.299)	2.357	(0.260)	2.285	(0.311)
μ_4	2.876	(0.258)	2.590	(0.301)	3.294	(0.263)	3.265	(0.313)
Number of observations	1932		1580		1932		1580	
P-value regional dummies	0.000		0.095		0.000		0.006	
Log Likelihood	-2627.33		-2254.90		-2375.68		-1942.77	
Pseudo R^2	0.1486		0.1110		0.2337		0.2095	

Chapter 6

The Determinants and Effects of Work Related Training in Britain

6.1 Introduction

There has been little empirical research on the determinants and effects of work related training in Britain. Most of the research that has taken place has focused on the impact of Government training schemes such as the Youth Training Scheme (YTS) or formal educational qualifications. There has been much less research on the determinants and effects of employer provided training and other forms of work related training which is by far the most common form of post educational training. The studies which have looked at this issue were reviewed in Chapter 2.

This paper uses a sub sample of the individuals used in the previous Chapter drawn from the British National Child Development Survey (NCDS) to look at the determinants and effects of different types of work related training in Britain. In this Chapter we once again use information from all five waves of the NCDS and focus on the same set of individuals who were employees in 1981 (when they were aged 23) and 1991 (when they were aged 33). We look at what factors were influential in determining whether or not an individual received training and the returns to this training and earlier education over the 10 year period between 1981 and 1991.

In this Chapter we use the data to look at a number of issues. The first is to establish who actually receives training and whether different types of training are taken by different individuals. The second is to look at the impact this training and earlier education has on the wage profile of these individuals over the 10 year period between 1981 and 1991. We look at whether the returns to education estimated in the previous Chapter change when account is also taken of individual's work related training experience. The final issues is to look at gender wage differentials and see how important the different training experiences of men and women are in explaining observed differences in the wages received by men and women.

As we saw in the last Chapter, we have information on the person's highest formal educational qualification at age 23 in 1981. We also have detailed information on the two highest qualifications they have obtained between 1981 and 1991 which we will call qualification training courses (QTCs). We distinguish such qualification training courses (QTCs) from other work related training courses (WRTCs). For the QTCs we only use information on the highest qualification ever obtained in one of these courses and whether a person has undertaken more than one QTC. For WRTCs we have information only for the 3 most recent courses lasting at least 3 days which have been undertaken between 1981 and 1991, although we know whether people have taken more than three WRTCs. For these WRTCs we distinguish on-the-job and off-the-job employer provided training courses (EPTCs)[1], from those undertaken privately (PTCs) or as part of a Government scheme (GTCs). We can also identify whether the training was undertaken while the person was with their current employer or not. This allows us to examine the interactions between different forms of formal education and different types of

[1]On-the-job EPTCs we define as those taken at the employer's premises whereas off-the-job EPTCS are those taken at a training or skills centre.

training.

We find that between 1981 and 1991, men have a substantially higher probability of undertaking both employer provided and qualification training courses than women in our sample. We also find that people who had received employer provided training in their 1981 job, had a higher probability of receiving both types of training. Family background variables, which were found to be important in determining educational outcomes in the last Chapter, are important in determining participation in QTCs, though less important in determining participation in EPTCs.

The results of this Chapter suggest that different types of training schemes have a positive and significant effect on individuals' wage outcomes. They also suggest that it is important to control for correlated transitory and to a lesser extent correlated permanent effects. The results suggest that for men, bad productivity shocks are associated with participation in employer provided training schemes. By not controlling for this, we would underestimate the returns to such EPTCs. This does not appear to be the case for women. Employer provided training has the biggest impact on the wages received by relatively well educated men and middle educated women. Men and women with only O Levels or less by 1981 receive no returns to employer provided training.

Participation in qualification training courses also appears to be correlated with transitory shocks and once again, estimates which do not take this into account underestimate the returns to such qualifications for both men and women. Most types of qualification training courses undertaken since 1981 are found to have significant effects on the wage outcomes of both men and women once we have controlled for correlated transitory effects.

The results also show that there are again large and significant returns to educational qualifications obtained prior to 1981 and our IV estimates are once again above conventional OLS estimates, even when controlling for correlated permanent effects like ability. It is also apparent from the Chapter that the estimated returns found to these qualifications in the previous Chapter are probably too high. Part of the returns to education found in the last Chapter appears instead to be attributable to returns to work related training rather than education. It is also appears that the different training experiences of men and women play some role in explaining the observed gender wage differentials in our sample.

In Section 2 we discuss the major features of the data used in our analysis. The analytical framework we use for estimating the returns to training is discussed more fully in Section 3. Section 4 presents the results of our analysis and conclusions are offered in Section 5.

6.2 The NCDS Data

6.2.1 Introduction

As we saw in the previous Chapter, the National Child Development Survey (NCDS) is a continuing longitudinal survey of persons living in Great Britain who were born between 3 and 9 March, 1958. The survey has detailed information on each individual's educational background as well as a large amount of information on family background variables. These variables were described in the previous Chapter and are all again used in the work of this Chapter.

The NCDS also has a large amount of information on an individual's training history which is the key focus of this Chapter.

6.2.2 Training measures in the NCDS

It is clear from the Chapter 2 that the types of training which have been the subject of empirical research differ in a number of important respects and in forming any general conclusions about the determinants and effects of training it is crucial to establish exactly what type of "training" we are talking about.

In our study we use a fairly wide definition of the word "training", but generally distinguish it from formal school and post-school education taken before individuals entered the labour market (which we refer to as "education")[2]. With "training" we distinguish between qualification training courses (QTCs) and work related training courses (WRTCs). Qualification training courses are defined to be courses undertaken by the individual after first commencing work which lead to a formal qualification. Work related training courses cover on- and off-the-job employer provided training courses, government training schemes and private training courses which were undertaken after the individual first entered the labour market.

The NCDS5 data provides us with a number of measures of training received by the individual between 1981 and 1991. It first asks respondents whether "...[s]ince March 1981 have you been on any courses that were meant to lead to qualifications". If the respondent has, it then moves on to ask detailed information about the two courses leading to the highest qualifications. It asks information on when the course started, how long it was meant to last, the reason for taking the course, where the course was taken, whether it was full- or part-time, which qualification the course was meant to lead to, whether the respondent obtained qualifications from the course and if they did the nature of the qualifications. It also asks whether the course was provided by the respondents employer at the time, whether any fees were provided by the employer, whether the course was completed, whether the person has started any job since leaving the course, whether the course was an entry requirement for any job the cohort member has done since, whether the respondent thought the course helped them get any job since and the respondents overall satisfaction with the course.

The questionnaire then moves on to ask about other work related training courses. In particular it asks whether "[s]ince March 1981 have you been on

[2]Hence the qualification variables used in the last Chapter are treated as "education" rather than "training".

any training courses designed to help you develop skills that you might use in a job" apart from the qualification courses which were asked about earlier. The questionnaire then establishes whether any of these courses lasted at least 3 days in total and if so how many training courses lasting at least 3 days they have started since March 1981.

The survey then asks the same set of detailed questions which were asked about the two highest qualification courses in respect of *the three most recent work related training courses.* The way we use this information to construct our training dummy variables is discussed in more detail below. Clearly, however, our measures of work related training are going to be very different to those used by Lynch [117] by virtue of the fact that the NCDS asks information on training courses lasting at least 3 days whereas the NLSY data used by Lynch only refers to courses lasting at least one month. Similarly our measures of training will not pick up things like "self-instruction" which is counted as training in the GHS.

The NCDS4 survey also has a number of questions on work related training received up until 1981. In the apprenticeship and training section of the questionnaire it has information on formal apprenticeships including whether the apprenticeship had been successfully completed by 1981. The training questions asked in this section identify whether the respondent has been on any training courses during any job which involved at least 14 days or 100 hours attendance either at a college, training centre or skill centre including training centres at the person's place of work. For such courses it only asks questions for the first three such courses. These are the training questions used in the study by Tan et. al. [153].

There are however, additional training questions asked in the employment section of the survey. We know whether the person received any training of any kind in their first job, and if they have held more than one job, in their 1981 job. If they had, they were asked whether the training they received was just showing them what the job was when they first started or whether it was more than this. If it was more than this they were asked whether the training took place at either a college or a training centre (including a training centre at the person's place of work). In our study we utilise the training questions from the employment section of the questionnaire rather than the training section in order to ensure that we obtain information on any training received in the person's 1981 job. These questions were also relied on by Blanchflower and Lynch [26] in their study.

6.2.3 Training Variables used in the analysis

In this paper a person is said to have undertaken training between 1981 and 1991 if they have undertaken any course designed to help them develop skills which might be of use in a job. If a person has taken a qualification course since 1981 we record information on the course leading to the highest qualification. We use similar qualification categories as we used in the previous Chapter for the highest post-school qualification except now we do not distinguish schooling qualifications such as O and A Levels. Once again these QTCs are clearly ordered. A description of our highest qualification variable for courses undertaken since 1981 is given in Table 6.1.

People who have done more than one qualification training course since 1981 are also separately identified. We also have information on the number of other work related training courses of at least 3 days which the person has undertaken in the last 10 years including detailed information on the three most recent courses completed. This allows us to distinguish both on- and off-the-job employer provided courses (EPTCs) from those undertaken privately (PTCs) or as part of a Government scheme (GTCs). In our sample most of the training courses undertaken are EPTCs. On-the-job EPTCs are defined to be those undertaken at the employers premises and off-the-job EPTCs as those taken at training colleges/centres which are not based at the employers premises.

Table 6.1: Description of Highest Training Qualification Variables

Variable	Description
Highest Qualification undertaken since 1981:	
Degree	University or CNAA first degree, CNAA Post-graduate Diploma, or University or CNAA Higher Degree.
Higher Vocational	Highest Vocational: Full professional qualification, part of a professional qualification, Polytechnic Diploma or Certificate (not CNAA validated), University or CNAA Diploma or Certificate, Nursing qualification including nursery qualification, non-graduate teaching qualifications, Higher National Certificate (HNC) or Diploma (HND), BEC/TEC Higher Certificate or Higher Diploma, City and Guilds Full Technological Certificate.
Middle Vocational	Middle Vocational: City and Guilds Advanced or Final, Ordinary National Certificate (ONC) or Diploma (OND), BEC/TEC National, General or Ordinary, or A level qualification.
Lower Vocational	Lower Vocational: City and Guilds Craft or Ordinary, a Royal Society of Arts (RSA) awards, stage 1, 2 or 3 or other commercial or clerical qualifications, O Level qualifications
Other	Miscellaneous Qualifications: All other courses leading to some sort of qualification which are not identified above.
None	No qualifications completed since 1981.

It has been argued that EPTCs are more likely to be firm specific than the other types of training courses. Hence any advantage in terms of a higher wage from undertaking an EPTC may depend on whether the person is still with the employer who trained them. To look at this issue we distinguish persons who are still with the employer who provided the most recent training course from those who have changed jobs since their last training course to see whether EPTCs are more firm specific than other types of training. We also can distinguish between EPTC and QTC courses commenced prior to 1989 and those commenced after that time. There are important methodological implications if training commenced prior to 1989 has a different impact on wages to that commenced since 1989 and this is discussed more fully in the next section.

We also have information on EPTCs undertaken by people in the job they held in 1981 as well as their first ever job if individuals have had more than one job by 1981[3].

[3]People were deemed to have undertaken an EPTC if they had received any training of any kind from their employer in their first and/or current job and this was more than just showing the person what their job involved when they first started.

6.2.4 Work History Variables

From the NCDS4 survey we construct variables identifying the number of children the respondent had living with them, whether they were married, whether their 1981 job was in the private sector, the region in which they lived, their 1981 weekly hours of work, their 1981 social class, the size of their 1981 employer, whether they were union members and the time in years they had been in their 1981 job and their labour market experience at the age of 23. From the 1991 NCDS5 survey, we also identify whether the person has been promoted in their current job and the person's total labour market experience at the time they were interviewed in 1991.

6.2.5 The Final Sample

This leaves is with a final sample of 1453 males and 1002 females. Summary statistics for our sample are given in Table 6.13 in Appendix A.6.1. Again, as was the case in the last Chapter, the sample under-represents individuals in the bottom quintiles of the verbal and arithmetic ability tests undertaken when the child was 7. There is also some evidence, that the sample of women we consider in this Chapter are more highly qualified than the women considered in the previous Chapter.

6.3 Methodology

6.3.1 Introduction

Our aim is to look at the impact of different types of education and training on individual wage outcomes over the 10 years between 1981 and 1991. There are a number of alternative approaches to the statistical analysis of the impact of training on wages. They again, like the returns to education literature, relate primarily to the issue of correcting for biases that can result from the correlation of unobservable individual characteristics "unobservables" with the incidence of training. We are in a particularly attractive position in this respect since the NCDS data gives us observations on wages before and after recent training spells as well as information on previous training spells, current and past employer characteristics, schooling and family background information, and the results of ability tests when the person was very young.

There are two possible sources of bias in evaluating training schemes. Both relate to the correlation of unobservables in the wage or earnings equation to the measures of training. For this discussion it is best to envisage a wage equation in which the unobservable components – which generate the estimation problem in the first place – are decomposed into a permanent effect and a transitory shock. For the sake of interpretation the permanent effect can be thought of as made up of unobserved ability and the transitory shock as an unexpected change in productivity.

The first source of bias relates to the possibility of correlation of training with unobserved *permanent* individual effects. This occurs where some individuals have unobservable attributes that not only mean they benefit more from training but also that they are more likely to undertake training schemes. Correction for this type of bias can take two forms. Either one can first difference the model to eliminate the individual effects or one can use the family background and other historic variables associated with the individual to proxy the permanent effect. The NCDS data base allows both of these possibilities since it provides detailed historic information on the individual including ability tests at age 7 as well as information on previous wages. First differencing has the attraction of eliminating individual effects based only on the assumption that they are constant over time. No further specification of the form of such effects is required. However, without further adjustment, it requires training to be exogenous to productivity shocks and also comes at the cost of inflating the influence of measurement error.

The second form of bias directly relates to the presence of temporary shocks to wages that are correlated with the participation in training or earlier education. Indeed, a "bad" productivity shock may lead to entry into a training programme and training becomes spuriously correlated with low wages – at least in the short run. To correct for the resulting downward bias in returns we need "instruments" for training and earlier "education" that are uncorrelated with the shock but correlated with training. We use the same instruments for education that we used in the previous Chapter. We also argue that the characteristics of previous employers are possible choices as instruments for training received between 1981 and 1991 as these are typically correlated with training but can be argued to have no direct role in a wage equation.

Finally, it is possible to combine both possibilities and correct for the presence of "productivity" shock bias and unobservable "ability" bias. It turns out that controlling for both of these biases induces changes in the estimates of the returns to education and training in the expected way. Rather than presenting a single set of results we provide a complete description of the estimates of the returns under each alternative specification. In our empirical results below it turns out that controlling for these biases is critical in gaining a correct evaluation of the returns to the different education and training schemes that have been undertaken by individuals in the NCDS.

6.3.2 A Model for Training and Earnings

The Wage Equation

We begin by writing a general sequential model of the evolution of training and wages as:

$$w_{0i} = x'_{0i}\beta_{00} + \sum_{k=1}^{m0} \alpha_{0k} D_{0ki} + f_i + \varepsilon_{0i} \tag{6.1}$$

$$w_{1i} = x'_{0i}\beta_{10} + x'_{1i}\beta_{11} + \sum_{k=1}^{m0} \alpha_{1k} D_{0ki} + \sum_{k=1}^{m1} \gamma_{1k} D_{1ki} + f_i + \varepsilon_{1i} \tag{6.2}$$

$$
\begin{aligned}
w_{2i} &= x'_{0i}\beta_{20} + x'_{1i}\beta_{21} + x'_{2i}\beta_{22} + \sum_{k=1}^{m0} \alpha_{2k} D_{0ki} + \sum_{k=1}^{m1} \gamma_{2k} D_{1ki} \\
&\quad + \sum_{k=1}^{m2} \psi_{2k} D_{2ki} + f_i + \varepsilon_{2i}
\end{aligned} \tag{6.3}
$$

where:

$w_{ti} =$ log real hourly wage at time t of individual i, where $t = 0$ (time of first job), $t = 1$ (1981) or $t = 2$ (1991)

$x_{0i} =$ vector of individual characteristics excluding training acquired before first job

$x_{1i} =$ vector of individual characteristics excluding training acquired between first job and 1981

$x_{2i} =$ vector of individual characteristics excluding training acquired between 1981 and 1991

$D_{0ki} =$ formal education received before first job

$D_{1ki} =$ training received between first job and 1981

$D_{2ki} =$ training received between 1981 and 1991

$f_i =$ unmeasured time invariant "permanent" personal attributes

$\varepsilon_{ti} =$ random errors at time t

The returns to training undertaken between 1981 and 1991 are given by the coefficients ψ_{2k}, $k = 1, 2...m2$ where $m2$ is the number of different training schemes undertaken between 1981 and 1991. Clearly the interpretation of the impact of training might depend on when the training took place. If a person who undertakes training just gets a once off increase in the *level* of their wage and the training has no impact on subsequent wage *growth* then issues of when the training took place over the 1981 to 1991 period are unimportant. If, however, training affects both the initial level *and* subsequent growth of the wage, then training received earlier in a persons working career should have a greater impact than training received more recently, i.e. ψ_{2k} will vary depending on the timing of training. To test this hypothesis that training affects wages in a once off permanent fashion, in our empirical work we will distinguish between training commenced before 1989 and training commenced after that time.

The impact on the 1991 wages of training received prior to the individual's first job, the education variables used in the last Chapter which reflect school and post-school formal qualifications[4] are given by α_{2k} and for training received between the first job and 1981 by the γ_{2k}. Typically we do not observe the initial wage w_{0i} but we do observe most of the other variables in this sequential model. The usefulness of this framework derives from our interest in eliminating correlation between the permanent individual effect f_i and the transitory shock ε_{2i} with participation in training by individual i between $t = 1$ and $t = 2$ which is represented by the D_{2ki}.

Controlling for Correlated Permanent Effects

If the unmeasured time invariant individual fixed effects f_i are correlated with the D_{2ki}, (or indeed any variable on the right hand side of equation (6.3) including earlier education or training) then OLS estimation of (6.3) will yield coefficient estimates which are biased. A standard approach to the elimination of fixed effects is to take first differences resulting in:

$$\begin{aligned} \Delta w_{2i} &= (\beta_{20} - \beta_{10})' x_{0i} + (\beta_{21} - \beta_{11})' x_{1i} + {\beta_{22}}' x_{2i} \\ &+ \sum_{k=1}^{m0} (\alpha_{2k} - \alpha_{1k}) D_{0ki} + \sum_{k=1}^{m1} (\gamma_{2k} - \gamma_{1k}) D_{1ki} \\ &+ \sum_{k=1}^{m2} \psi_{2k} D_{2ki} + (\varepsilon_{2i} - \varepsilon_{1i}) \end{aligned} \tag{6.4}$$

This is the traditional fixed effect model which was used in the studies by Lynch [117], Greenhalgh and Stewart [80] and Blanchflower and Lynch [26]. If observed individual characteristics such as the x_{0i} affect w_{2i} and w_{1i} in the same way (as we assume for the unobserved individual effects) then $\beta_{10} = \beta_{20}$ and the coefficients on the x_{0i} will be zero. Similarly if pre-work training D_{0ki}, affects wage outcomes in 1981 and 1991 identically then $\alpha_{1k} = \alpha_{2k}$. Clearly these are testable restrictions of the model.

[4] In this Chapter we only consider the returns to formal qualifications and not to years of education.

The drawback of the first differenced specification lies in the MA error specification $(\varepsilon_{2i} - \varepsilon_{1i})$. The training measured by D_{0ki} and D_{1ki} takes place before the shock in the period 1 wage is revealed and is possibly uncorrelated with ε_{1i}. However recent training, D_{2ki} is quite possibly influenced by ε_{1i}. It is therefore difficult to argue that $(\varepsilon_{2i} - \varepsilon_{1i})$ is uncorrelated with D_{2ki}. Past shocks to wages, at least, might be expected to induce participation in training.

An alternative to first differencing is to proxy the fixed effects f_i as

$$\mathrm{E}(f_i|P_i, W_i) = P_i'\pi \tag{6.5}$$

where P_i are observable variables which proxy ability and W_i all the other variables appearing on the right hand side of our wage equation. We then assume that conditional on these variables, $f_i - \mathrm{E}(f_i|P_i, W_i)$ is uncorrelated with the training variables entering the wage equation. Most longitudinal data bases do not carry detailed historic individual information, especially variables measuring ability, but the NCDS does and therefore an extended regression we may run is simply

$$\begin{aligned} w_{2i} = {} & x_i'\beta + \sum_{k=1}^{m0} \alpha_{2k} D_{0ki} + \sum_{k=1}^{m1} \gamma_{2k} D_{1ki} \\ & + \sum_{k=1}^{m2} \psi_{2k} D_{2ki} + \tilde{\varepsilon}_{2i} \end{aligned} \tag{6.6}$$

where $\tilde{\varepsilon}_{2i} = f_i - E(f_i|P_i, W_i) + \varepsilon_{2i}$ and we have combined in x_i all the x_{ji} and P_i variables entering the wage equation. As we saw in the previous Chapter, if our proxies of ability and training variables are both measured with error, then the biases arising from using the proxies could be worse than if we simply omitted measures of ability. In the work in that Chapter, however, we found little evidence of measurement error in our measures of ability and we therefore just enter our measures directly into our wage equations.

In this specification the only remaining possible bias on returns to training results from the potential correlation of *current* shocks ε_{2i} with training. For this we turn to a discussion of transitory shocks.

Controlling for Transitory Shocks

The above estimator is only consistent if self-selection into training is done on the basis of permanent unobserved individual effects. However, we have argued that it is quite possible that transitory shocks to productivity are also correlated with participation in training. In the previous Chapter we also saw that current unobserved individual effects were correlated with education. The productivity shock bias arises through the correlation of D_{2ki} and $\widetilde{\varepsilon}_{2i}$ in (6.6) or alternatively D_{2ki} with ε_{2i} and ε_{1i} in (6.4). This results in a downward bias in estimated returns. The bias we observed in the previous Chapter arises through the correlation of D_{0ki} and $\widetilde{\varepsilon}_{2i}$ in (6.6) or alternatively D_{0ki} with ε_{2i} and ε_{1i} in (6.4). This was also found to result in a downward bias.

To control for the transitory shock bias we need an instrument that while correlated with the training variables D_{2ki} is uncorrelated with the productivity shocks $\widetilde{\varepsilon}_{2i}$ in specification (6.6) and ε_{1i} and ε_{2i} in the first differenced specification (6.3). Family background variables as well as 1981 employer characteristics as mentioned earlier, would seem a good choice for this. Given these instruments we can perform the usual selectivity corrections of Heckman [97] for the two models of the previous sub-section.

6.3.3 The Estimating Equations

Following the discussion above we estimate four different wage equation specifications. Our first specification (i) is to perform OLS on the levels equation (6.6). The second specification (ii) is to perform OLS on the first difference model (6.4) which controls for correlated permanent effects. Both these specifications do not control for correlation between transitory shocks and training or transitory shocks and education.

In controlling for transitory shocks we write the characteristics that are used to control or instrument the training variables as c_{2i}. Training participation is then determined by

$$D^*_{2ki} = z'_{2i}\zeta_k + \upsilon_{ki} \tag{6.7}$$

where $z^{'}_{2i} = (x'_{0i}, x'_{1i}, c^{'}_{2i})$ and:

$$D_{2ki} = 1 \text{ if } D^*_{2ki} \geq 0 \text{ i.e. } \upsilon_{ki} \geq -z'_{2i}\zeta_k \tag{6.8}$$

$$D_{2ki} = 0 \text{ if } D^*_{2ki} < 0 \text{ i.e. } \upsilon_{ki} < -z'_{2i}\zeta_k \tag{6.9}$$

In estimation we use an ordered probit for the highest qualification course undertaken since 1981 and a univariate probit model to estimate participation in employer provided training. From these we can, following Heckman [97], calculate the selection adjustment terms for the correlated transitory shocks. For the univariate probit model this is given by:

$$\lambda_{D2ki} = \frac{\phi(z'_{2i}\widehat{\zeta}_k)}{\Phi(z'_{2i}\widehat{\zeta}_k)} \text{ if } D_{2ki} = 1 \tag{6.10}$$

$$\lambda_{D2ki} = \frac{-\phi(z'_{2i}\widehat{\zeta}_k)}{1 - \Phi(z'_{2i}\widehat{\zeta}_k)} \text{ if } D_{2ki} = 0 \tag{6.11}$$

where $\phi(.)$ is the normal probability distribution function and $\Phi(.)$ the cumulative normal distribution function. We undertake an ordered probit for the highest education qualification undertaken by the age of 23 following exactly the same approach as used in the previous Chapter and calculate the selection term, λ_{D0i}, from this ordered probit. We treat work related training undertaken before the age of 23, D_{1ki}, as exogenous as we have no suitable instruments for this training.

Specification (iii) is a model which controls for these transitory shocks in the levels specification and is given by:

$$\begin{aligned} w_{2i} = {} & x'_i\beta + \sum_{k=1}^{m0} \alpha_{2k} D_{0ki} + \sum_{k=1}^{m1} \gamma_{2k} D_{1ki} + \sum_{k=1}^{m2} \psi_{2k} D_{2ki} \\ & + \sigma_0 \lambda_{D0i} + \sum_{k=1}^{m2} \sigma_{2k} \lambda_{D2ki} + \widetilde{\varepsilon}_{2i} \end{aligned} \tag{6.12}$$

Our final specification (iv) controls for correlated unobserved fixed effects (by first differencing), as well as the transitory shocks and is given by:

$$\begin{aligned}\Delta w_{2i} &= x'_{0i}(\beta_{20}-\beta_{10}) + x'_{1i}(\beta_{21}-\beta_{11}) + x'_{2i}\beta_{22} \\ &+ \sum_{k=1}^{m0}(\alpha_{2k}-\alpha_{1k})D_{0ki} + \sum_{k=1}^{m1}(\gamma_{2k}-\gamma_{1k})D_{1ki} \\ &+ \sum_{k=1}^{m2}\psi_{2k}D_{2ki} + \rho_0\lambda_{D0i} + \sum_{k=1}^{m2}\rho_{2k}\lambda_{D2ki} + (\varepsilon_{2i}-\varepsilon_{1i})\end{aligned} \tag{6.13}$$

It should also be noted that in this model the variables entering the selection terms λ_{D2ki} and λ_{D0i} have to be uncorrelated with both ε_{2i} *and* ε_{1i}. While 1981 firm characteristics, which are instruments for the training selection terms, are unlikely to be correlated with ε_{2i} they are possibly correlated with the ε_{1i}. Such correlation would typically induce a downward bias in the returns to training coefficients and should be borne in mind when interpreting the results from this specification. The four wage equation specifications that we use in the next section are summarised in Table 6.2.

6.3.4 Training and Gender Wage Differentials

We can follow the methodology of Chapters 3 and 5 and decompose the observed gender wage differential into that which is attributable to differences in observed characteristics of men and women, and that attributable to women and men being paid different prices for a given set of characteristics. In this Chapter we extend this decomposition and look at these two effects when work related training is and is not taken into account. This will enable us to gauge the importance, for example, of differences in the work related training experiences of men and women in explaining observed gender wage differentials.

Table 6.2: Wage Equation Specifications

Specification (i):

$$w_{2i} = x_i'\beta + \sum_{k=1}^{m0} \alpha_{2k} D_{0ki} + \sum_{k=1}^{m1} \gamma_{2k} D_{1ki} + \sum_{k=1}^{m2} \psi_{2k} D_{2ki} + \widetilde{\varepsilon}_{2i}$$

Specification (ii):

$$\Delta w_{2i} = x_{0i}'(\beta_{20}-\beta_{10})+x_{1i}'(\beta_{21}-\beta_{11})+x_{2i}'\beta_{22}+\sum_{k=1}^{m0}(\alpha_{2k}-\alpha_{1k})D_{0ki}+ \sum_{k=1}^{m1}(\gamma_{2k}-\gamma_{1k})D_{1ki} + \sum_{k=1}^{m2}\psi_{2k}D_{2ki} + (\varepsilon_{2i}-\varepsilon_{1i})$$

Specification (iii):

$$w_{2i} = x_i'\beta + \sum_{k=1}^{m0} \alpha_{2k} D_{0ki} + \sum_{k=1}^{m1} \gamma_{2k} D_{1ki} + \sum_{k=1}^{m2} \psi_{2k} D_{2ki} + \sigma_0\lambda_{D0i} + \sum_{k=1}^{m2}\sigma_{2k}\lambda_{D2ki} + \widetilde{\varepsilon}_{2i}$$

Specification (iv):

$$\Delta w_{2i} = x_{0i}'(\beta_{20}-\beta_{10})+x_{1i}'(\beta_{21}-\beta_{11})+x_{2i}'\beta_{22}+\sum_{k=1}^{m0}(\alpha_{2k}-\alpha_{1k})D_{0ki}+ \sum_{k=1}^{m1}(\gamma_{2k}-\gamma_{1k})D_{1ki} + \sum_{k=1}^{m2}\psi_{2k}D_{2ki} + \rho_0\lambda_{D0i} + \sum_{k=1}^{m2}\rho_{2k}\lambda_{D2ki} + (\varepsilon_{2i}-\varepsilon_{1i})$$

6.4 Results

6.4.1 Introduction

In this section we use the models developed above to estimate the determinants of and returns to different forms of training. The exogenous explanatory variables, (x_{ji}), that we use in wage equations once again consist of gender and regional dummy variables. In estimating our levels equations we also include our verbal and arithmetic ability dummy variables.

The pre-work training dummy variables D_{0ki}, identify the individual's highest "education" qualification, that is their highest school and post-school qualifications obtained by 1981 when aged 23 years. Our D_{0ki} variables, therefore, reflect formal educational qualifications (of type k) which have generally been obtained before the individual (denoted by i) commences work (i.e. at time $t = 0$). These are the same variables that were considered in the previous Chapter.

Our D_{1ki} variables identify work related training (of type k) received by the individual (denoted by i) between their first and 1981 job (i.e. at time $t = 1$). The D_{2ki} variables distinguish work related training courses (WRTCs) and qualification training courses (QTCs) undertaken between 1981 and 1991 (i.e. at time $t = 2$).

For WRTCs we distinguish between employer provided training courses (EPTCs), private training courses (PTCs) and government training courses (GTCs). As mentioned earlier, the NCDS data has detailed information on only the three most recent WRTCs taken by the individual. This information allows us to distinguish training which was taken while the individual was with their current employer from that undertaken with previous employers. EPTCs are by far the most important form of non-qualification work related training in our sample and we observe only a few people who have undertaken PTCs or GTCs in their last three training courses. We distinguish EPTCs that were taken at the employer's premises (on-the-job EPTCs) from those undertaken away from the premises at a training centre (off-the-job EPTCs). Our EPTC dummy variables are not mutually exclusive for people who have undertaken different types of EPTCs. If we wish to estimate the return to taking on-the-job EPTC(s) with a current employer and off-the-job EPTC(s) with a previous employer then we will have to add the coefficients on each of these variables to obtain the estimated return. In our analysis we also separately identify people who have undertaken more than three WRTCs. We also know when the respondent started their QTC and/or EPTCs so that we can look at whether the timing of training has implications when estimating the returns to different types of training. To do this we distinguish between courses commenced prior to 1989 and those started in 1989, 1990 or 1991[5].

6.4.2 The determinants of Training

As mentioned earlier, by far the most common form of training undertaken by the NCDS cohort are employer provided training courses (EPTCs) and qualification training courses (QTCs). In looking at the determinants of training we therefore only consider these two types of training and treat government and private training courses as exogenous. Table 6.3 presents the probit equation for employer provided training and the ordered probit equation for the highest qualification training course for males and females separately. Results for the whole sample are given in Table 6.14 in Appendix A.6.2. To avoid problems of simultaneous determination of training choices and other labour market outcomes, the explanatory variables we use in the probits consist entirely of individual characteristics observed in waves of the NCDS prior to 1991. Clearly these variables are, by definition, predetermined when training decisions between 1981 and 1991 were made. As explained in the previous section, these variables must include our "instruments" for training,

[5] We tried a number of timing splits but the results fairly robust to different specifications.

which we denoted by c_{2i}. The instruments we use are the characteristics of the individual's employer in 1981 such as employer size and whether it was a private sector firm as well as other individual characteristics at 1981 such as the number of children the individual had living with them, whether they were married, the hours they were working, their social class, whether they were a union member and the years they had been with their 1981 employer. We also use family background variables from NCDS3 which were found to be important in determining educational outcomes in the previous Chapter. We argue that these variables will be correlated with training undertaken between 1981 and 1991 but have no direct role in a wage equation[6].

Broadly speaking we use four categories of variables in explaining the determinants of training. These variables are largely in accordance with variables used in the studies reviewed in Chapter 2. The first relates to early family background variables. These were found to be important in determining educational outcomes and could be important if they indeed capture the extent of earlier human capital accumulation. Factors such as years of education undertaken by the person's mother and father are important since it is very likely that the parents influence their children directly or as role models[7].

The next group of variables are those describing the training that the worker had received by 1981. The justification for these variables is that earlier training experiences may effect the ease with which new training is undertaken. Next we have a set of individual characteristics relating to the individuals family and regional status, and occupation as at 1981. These are important for a number of reasons. To the extent that training increases the hours spent in the labour market one might expect that, say, marital status

[6]In earlier versions of our work we also used regional unemployment rates and industry dummy variables. These were found not to be significant and reduced our sample size significantly and therefore are not included here.

[7]The impact of these variables are not reported in Table 6.3 for reasons of parsimony. We instead include the P-value from an F-test of their significance in the various equations.

or the number of children might affect the training choice through their effect on marginal value of non-market time and tend to reduce it. An offsetting factor, particularly if individuals are liquidity constrained, comes from the high consumption demands that a large family is likely to generate. Such demands may lead to activities that enhance human capital development. The region in which an individual lives may also be important in determining access to certain types of training. The occupational variables reflect the access to training, the need to do so and also indirectly the wealth of the individual. Increased wealth is likely to make access to training easier than for individuals who are liquidity constrained since some forms of training will have to be financed by the individuals themselves (either through lost earnings and/or directly through fees).

The final set of variables are the characteristics of the firm where the individual worked in 1981. These are likely to affect training outcomes through different access opportunities. Setting up training courses may involve considerable fixed costs therefore one might expect large employers and/or public sector employers to provide training more routinely.

The variables we use in explaining the determinants of training are broadly in accordance with previous studies looking at this question. The major difference between our study and previous studies is that we use individual characteristics that were determined before current training took place. Most of the studies reviewed above, for instance, include current employer size as a determinant of training. Current employment size is not a valid variable, however, if individuals choose the type of employer in order to obtain training. If this occurred current firm size could lead to a serious simultaneity bias in the results. On the other hand 1981 firm characteristics are only informative if there is some degree of persistence in the data which would imply that past firm characteristics are correlated with current ones. Whether this is the case is an empirical question. Previous studies have also treated early education as exogenous and included them directly in their reduced form training equations.

Individuals who have undertaken EPTCs in 1981 are more likely to obtain either EPTC or QTC training between 1981 and 1991. Both EPTCs and QTCs are more likely to be taken up by skilled workers and professionals than by the lower skilled workers. Workers who were in larger firms in 1981 are more likely to participate in an employer provided training between 1981 and 1991, but employer size does not impact on participation in QTCs. In addition people who are members of a union in 1981 are more likely to have undertaken EPTCs. This is also true of QTCs for men, though this effect is not significant at normal levels. Individuals who were in private sector firms in 1981 are less likely to have undertaken both EPTCs and QTCs between 1981 and 1991, though this finding is only significant for QTCs. Men who were married in 1981 were more likely to undertake EPTCs. Early family background variables are also important in explaining qualification training course participation.

From the results of these training equations we calculate our two selection terms $\lambda_{D2ki} = (\lambda_{eptc}, \lambda_{qtc})$. We also carry out ordered probits on the highest qualification obtained by the individual by the age of 23 in 1981. The explanatory variables in these equations are identical to those used in the previous chapter. The determinants of these qualifications for the sub-sample of individuals used in this Chapter are very similar to those found in the last Chapter. The results of these ordered probits are reported in Table 6.15 in Appendix A.6.3. We use the results from these ordered probits to once again construct a selection term $\lambda_{D0i} = \lambda_q$.

6.4.3 Estimates of the returns to highest qualifications

In this section we look at estimated the OLS and IV returns to qualifications for the sub-sample used in this Chapter so that we can make direct comparisons with the results obtained in the previous Chapter. The results

Table 6.3: Male and Female Training Participation

Variable	Employer Provided Training				Qualification Training			
	Males		Females		Males		Females	
	Coef.	(S.E.)	Coef.	(S.E.)	Coef.	(S.E.)	Coef.	(S.E)
Constant	-1.813	(0.581)	-1.506	(0.890)				
WRTCs by 1981:								
EPTC in 1981 job	0.404	(0.083)	0.523	(0.097)	0.278	(0.080)	0.199	(0.098)
EPTC in first job	0.005	(0.099)	0.041	(0.125)	-0.135	(0.094)	0.072	(0.120)
One job only 1981	0.280	(0.109)	-0.033	(0.127)	0.059	(0.103)	-0.004	(0.128)
No. of children 1981	-0.104	(0.092)	-0.233	(0.182)	0.069	(0.089)	-0.048	(0.167)
Married 1981	0.154	(0.082)	-0.063	(0.093)	-0.052	(0.078)	-0.048	(0.093)
Private Sector 1981	-0.074	(0.085)	-0.059	(0.108)	-0.183	(0.080)	-0.454	(0.109)
Hours in 1981 job	-0.004	(0.005)	0.008	(0.007)	0.001	(0.005)	0.003	(0.007)
Social Class 1981 job:								
Prof/Intermediate	0.770	(0.329)	0.795	(0.659)	0.609	(0.312)	0.694	(0.521)
Skilled non-manual	1.093	(0.329)	0.776	(0.653)	0.375	(0.312)	0.315	(0.516)
Skilled manual	0.320	(0.320)	0.474	(0.681)	0.159	(0.305)	0.593	(0.543)
Semi-skilled	0.554	(0.329)	0.151	(0.674)	0.056	(0.316)	-0.147	(0.544)
Firm size 1981 job:								
11 – 24	0.196	(0.146)	0.138	(0.162)	-0.026	(0.138)	-0.335	(0.162)
25 – 99	0.263	(0.127)	0.320	(0.150)	-0.100	(0.120)	-0.160	(0.147)
100 – 499	0.390	(0.130)	0.129	(0.154)	-0.028	(0.122)	0.151	(0.146)
500+	0.404	(0.131)	0.182	(0.157)	-0.044	(0.123)	0.147	(0.150)
Union Member 1981	0.150	(0.087)	0.248	(0.105)	0.129	(0.083)	-0.283	(0.105)
Years in 1981 job	-0.068	(0.027)	-0.018	(0.031)	-0.068	(0.026)	-0.058	(0.031)
Experience 1981	0.012	(0.031)	-0.030	(0.037)	-0.013	(0.030)	-0.012	(0.035)
Maths ability:								
2nd quintile	0.036	(0.130)	-0.076	(0.157)	0.191	(0.127)	0.321	(0.167)
3rd quintile	0.260	(0.133)	-0.116	(0.164)	0.070	(0.131)	0.153	(0.175)
4th quintile	0.266	(0.139)	-0.087	(0.166)	0.047	(0.138)	0.372	(0.173)
5th quintile	0.282	(0.146)	-0.004	(0.176)	0.061	(0.142)	0.282	(0.187)
Verbal ability:								
2nd quintile	-0.046	(0.129)	-0.089	(0.225)	-0.032	(0.131)	0.045	(0.222)
3rd quintile	-0.062	(0.145)	0.104	(0.224)	0.035	(0.145)	0.025	(0.223)
4th quintile	-0.177	(0.156)	0.078	(0.231)	0.136	(0.153)	0.048	(0.231)
5th quintile	-0.108	(0.172)	0.011	(0.241)	0.076	(0.168)	-0.147	(0.241)
μ_1					1.008	(0.535)	0.686	(0.780)
μ_2					1.266	(0.535)	0.861	(0.780)
μ_3					1.592	(0.536)	1.242	(0.781)
μ_4					1.730	(0.536)	1.389	(0.782)
μ_5					2.553	(0.538)	2.497	(0.788)
Number of observations	1453		1002		1453		1002	
P-value Ability Variables	0.3732		0.9405		0.742		0.378	
P-value 1981 Regional Vars	0.1945		0.4131		0.484		0.004	
P-value 1974 Family Vars	0.2513		0.3710		0.018		0.030	
Log Likelihood	-870.55		-573.67		-1475.54		-870.52	
Pseudo R^2	0.1348		0.1380		0.068		0.1174	

Table 6.4: The Returns to Education for Males and Females

Variable	Males				Females			
	OLS		IV		OLS		IV	
	Coef.	(S.E.)	Coef.	(S.E.)	Coef.	(S.E.)	Coef.	(S.E)
Constant	1.373	(0.127)	1.204	(0.131)	0.329	(0.095)	0.269	(0.095)
Highest Qualification 1981:								
Other	0.056	(0.042)	0.142	(0.046)	0.124	(0.050)	0.171	(0.051)
O Level	0.173	(0.037)	0.265	(0.042)	0.068	(0.038)	0.162	(0.047)
Lower Vocational	0.154	(0.033)	0.300	(0.043)	0.189	(0.047)	0.312	(0.058)
5 + O Levels	0.217	(0.045)	0.381	(0.054)	0.253	(0.041)	0.398	(0.059)
Middle Vocational	0.200	(0.030)	0.419	(0.054)	0.272	(0.045)	0.432	(0.067)
A Levels	0.353	(0.046)	0.608	(0.068)	0.510	(0.055)	0.672	(0.070)
Upper Vocational	0.333	(0.039)	0.642	(0.074)	0.606	(0.044)	0.815	(0.080)
Degree	0.543	(0.049)	0.945	(0.095)	0.869	(0.047)	1.141	(0.090)
Experience	0.010	(0.007)	0.014	(0.007)	0.056	(0.005)	0.057	(0.005)
Maths ability:								
2nd quintile	0.034	(0.033)	0.016	(0.033)	0.030	(0.037)	0.009	(0.037)
3rd quintile	0.041	(0.033)	0.009	(0.033)	0.045	(0.036)	0.020	(0.036)
4th quintile	0.093	(0.032)	0.055	(0.033)	0.049	(0.038)	0.014	(0.039)
5th quintile	0.127	(0.034)	0.061	(0.037)	0.038	(0.041)	-0.006	(0.041)
Verbal ability:								
2nd quintile	0.069	(0.030)	0.035	(0.031)	0.092	(0.045)	0.066	(0.046)
3rd quintile	0.060	(0.031)	0.003	(0.033)	0.138	(0.045)	0.098	(0.047)
4th quintile	0.114	(0.032)	0.028	(0.037)	0.140	(0.045)	0.073	(0.050)
5th quintile	0.103	(0.034)	0.005	(0.039)	0.171	(0.047)	0.086	(0.053)
λ_q			-0.121	(0.025)			-0.087	(0.027)
Number of observations	1453		1453		1002		1002	
P-value regional dummies	0.000		0.000		0.000		0.000	
P-value ability dummies	0.000		0.0.495		0.012		0.7280	
Log Likelihood	-531.64		-519.135		-344.33		-338.17	
R^2	0.2977		0.3097		0.4313		0.4383	

presented in Table 2.72 compare directly with our OLS and IV estimates obtained in the previous chapter for highest qualifications. The OLS results reported below are generally lower than those found in the previous Chapter, whereas the IV results are generally higher. We saw in the previous Chapter, for example, that our IV estimate of the return to a degree is around 89 per cent for men and just over 100 per cent for women compared to those with no qualifications. The IV estimates presented below are slightly higher for the sub-sample considered in this Chapter at 95 and 115 per cent respectively. Clearly by selecting on people who are in employment in 1981 and 1991 we obtain slightly different estimates to those obtained when we just selected on employment in 1991.

6.4.4 Estimates of the returns to training

We now turn to the results of the effects of training on wages. As explained in the theoretical section we need to address the issue of unobserved permanent individual effects and the effects of productivity shocks on training outcomes. Unobservable permanent individual effects may bias our results to the extent that a certain type of person (more or less able due to unobservables) has greater tendency to obtain certain types of education or training. The latter may arise if a productivity shock affects both wages and the decision to obtain training. The results up to now suggest that training is positively related to observed measures of individual ability. On this basis we can expect that it is also positively related to unobserved measures of ability. If this is the case then estimates that do not control for this will attribute too high an effect to training. On the other hand if negative wage shocks lead to more training this would lead to a negative bias on the training effect. The results for each of the four wage specifications outlined in Table 6.2 are presented in Table 6.5 for men and in Table 6.6 for women.

In the first and third columns of Table 6.5 we present the results in log-levels. In the second and fourth columns we present results where the dependent variable is in first differences of logs (i.e. approximately growth rates). In the latter case we control for unobserved fixed effects in the levels by considering the effects of training on wage growth and by implication on wage levels. In columns three and four we control for the effects of productivity shocks. This is achieved using the assumption that the 1981 firm and individual characteristics and early family background variables do not affect wages directly. This assumption is sufficient to identify the model. In the final column, where we also control for unobserved fixed effects we need the additional assumption that training in 1981 and all the other variables entering the reduced form training equations are not correlated with the productivity shocks.

In the results presented below we correct for the effect of correlated transitory shocks on employer provided training courses, qualification training courses and highest education qualifications. We treat employer provided training courses undertaken before the age of 23 as exogenous. All the wage equations contain regional dummy variables. Ability variables are also included in the two levels equations[8].

First looking at the coefficients of λ_{EPTC} in the last two columns of Table 6.5 it is clear that for men, employer provided training is correlated to current unobserved productivity shocks. When these are negative there is a greater tendency to obtain employer provided training. The results clearly indicate that the endogeneity of employer provided training cannot be ignored. If ignored we would tend to underestimate the effects of EPTCs. This can be seen by comparing columns one and three or columns two and four respectively. There is also evidence both qualification training courses and education are also endogenous. Our two methods of controlling for unobserved fixed effects give reasonably similar results which is also encouraging. The only noticeable difference is that the effect of on–the–job EPTCs undertaken with a person's previous have a larger effect in the fixed effect model, though both coefficients are reasonably imprecisely determined and are not significantly different from each other. Strictly speaking the results in column four (which control for fixed effects through differencing) are not more general than those in column three (where fixed effects are proxied by ability measures) since the former requires an extra assumption, namely that our training instruments are uncorrelated with both ε_{2i} *and* ε_{1i}.

The results suggest that for men, undertaking an EPTC with their current employer confers a significant wages advantage, particularly if the course is an off-the-job EPTC. The effects of training with a previous employer are

[8]When we exclude ability variables in our levels specification, the only estimates which are affected are the returns to education. The estimated returns to these qualifications are higher when ability variables are not included as was the case for the results presented in the previous Chapter. This is true for both men and women.

Table 6.5: Male Returns to Education and Training

Variable	(i)–w_{2i} Coef.	(S.E.)	(ii)–Δw_{2i} Coef.	(S.E.)	(iii)–w_{2i} Coef.	(S.E.)	(iv)–Δw_{2i} Coef.	(S.E)
Constant	1.412	(0.124)	0.168	(0.165)	1.194	(0.132)	0.017	(0.168)
WRTCs since 1981:								
Current Job:								
On–the–job EPTC(s)	0.044	(0.021)	0.063	(0.023)	0.083	(0.027)	0.087	(0.029)
Off–the–job EPTC(s)	0.115	(0.022)	0.078	(0.025)	0.159	(0.026)	0.113	(0.031)
Previous Job:								
On–the–job EPTC(s)	0.103	(0.041)	0.153	(0.057)	0.136	(0.042)	0.182	(0.057)
Off–the–job EPTC(s)	-0.001	(0.037)	-0.038	(0.042)	0.047	(0.040)	-0.008	(0.044)
PTC(s)	-0.012	(0.039)	-0.047	(0.040)	-0.016	(0.038)	-0.055	(0.039)
GTC(s)	-0.192	(0.076)	-0.145	(0.079)	-0.167	(0.074)	-0.123	(0.079)
>3 WRTCs	0.092	(0.025)	0.018	(0.028)	0.092	(0.025)	0.015	(0.028)
Only one job since 1981	0.005	(0.019)	-0.055	(0.021)	0.000	(0.019)	-0.056	(0.021)
Highest QTC since 1981:								
Other	-0.112	(0.036)	-0.072	(0.039)	-0.034	(0.052)	-0.039	(0.056)
Lower Vocational	0.010	(0.036)	0.032	(0.037)	0.106	(0.062)	0.074	(0.067)
Middle Vocational	0.074	(0.065)	0.106	(0.074)	0.180	(0.081)	0.147	(0.092)
Upper Vocational	0.148	(0.033)	0.144	(0.036)	0.270	(0.073)	0.190	(0.081)
Degree	0.087	(0.046)	0.085	(0.058)	0.277	(0.104)	0.160	(0.115)
More than one QTC	0.013	(0.031)	0.042	(0.034)	0.024	(0.031)	0.048	(0.034)
WRTCs by 1981:								
EPTC in 1981 job	0.069	(0.020)	0.007	(0.022)	0.045	(0.021)	-0.012	(0.023)
EPTC in first job	0.038	(0.021)	0.021	(0.023)	0.039	(0.021)	0.020	(0.023)
Highest Qualification 1981:								
Other	0.040	(0.042)	-0.038	(0.049)	0.100	(0.046)	0.009	(0.051)
O Level	0.120	(0.035)	0.063	(0.038)	0.176	(0.040)	0.089	(0.039)
Lower Vocational	0.103	(0.033)	-0.042	(0.038)	0.207	(0.043)	0.037	(0.044)
5 + O Levels	0.124	(0.042)	0.051	(0.045)	0.236	(0.052)	0.123	(0.050)
Middle Vocational	0.136	(0.030)	0.030	(0.035)	0.292	(0.054)	0.146	(0.048)
A Levels	0.245	(0.046)	0.093	(0.053)	0.418	(0.070)	0.222	(0.066)
Upper Vocational	0.205	(0.039)	0.025	(0.045)	0.419	(0.074)	0.199	(0.066)
Degree	0.419	(0.050)	0.098	(0.064)	0.689	(0.095)	0.319	(0.090)
Experience	0.004	(0.007)	0.064	(0.015)	0.012	(0.008)	0.062	(0.015)
Experience 1981			-0.122	(0.019)			-0.110	(0.020)
λ_q					-0.086	(0.024)	-0.077	(0.019)
λ_{eptc}					-0.051	(0.018)	-0.038	(0.020)
λ_{qtc}					-0.072	(0.035)	-0.031	(0.039)
Number of observations	1453		1453		1453		1453	
P-value regional dummies	0.000		0.000		0.000		0.000	
P-value ability dummies	0.000				0.654			
Log Likelihood	-453.26		-599.83		-438.83		-587.91	
R^2	0.3696		0.2483		0.3819		0.2605	

Table 6.6: Female Returns to Education and Training

Variable	Specification and Dependent Variable							
	(i)–w_{2i}		(ii)–Δw_{2i}		(iii)–w_{2i}		(iv)–Δw_{2i}	
	Coef.	(S.E.)	Coef.	(S.E.)	Coef.	(S.E.)	Coef.	(S.E)
Constant	0.528	(0.095)	-0.109	(0.103)	0.462	(0.095)	-0.177	(0.108)
WRTCs since 1981:								
Current Job:								
On–the–job EPTC(s)	0.073	(0.026)	0.063	(0.031)	0.090	(0.036)	0.059	(0.036)
On–the–job EPTC(s)	0.106	(0.029)	0.088	(0.030)	0.121	(0.036)	0.083	(0.039)
Previous Job:								
On–the–job EPTC(s)	0.046	(0.041)	0.023	(0.053)	0.052	(0.046)	0.014	(0.059)
On–the–job EPTC(s)	0.032	(0.045)	0.043	(0.052)	0.031	(0.048)	0.028	(0.058)
PTC(s)	0.117	(0.040)	0.075	(0.051)	0.108	(0.040)	0.066	(0.051)
GTC(s)	0.125	(0.093)	0.093	(0.085)	0.105	(0.090)	0.099	(0.091)
> 3 WRTCs	0.070	(0.031)	0.040	(0.033)	0.063	(0.031)	0.036	(0.032)
Only one job since 1981	0.121	(0.026)	0.009	(0.029)	0.120	(0.026)	0.009	(0.029)
Highest QTC since 1981:								
Other	0.039	(0.072)	0.088	(0.068)	0.146	(0.081)	0.152	(0.079)
Lower Vocational	-0.096	(0.042)	-0.030	(0.051)	0.028	(0.065)	0.037	(0.071)
Middle Vocational	0.058	(0.051)	0.099	(0.062)	0.231	(0.082)	0.192	(0.090)
Upper Vocational	0.155	(0.039)	0.205	(0.041)	0.318	(0.079)	0.296	(0.082)
Degree	0.106	(0.064)	0.150	(0.075)	0.342	(0.118)	0.279	(0.132)
More than one QTC	0.066	(0.042)	0.086	(0.047)	0.061	(0.042)	0.085	(0.048)
WRTCs by 1981:								
EPTC in 1981 job	0.007	(0.023)	-0.010	(0.025)	-0.010	(0.024)	-0.017	(0.026)
EPTC in first job	-0.036	(0.027)	0.022	(0.031)	-0.045	(0.027)	0.017	(0.032)
Highest Qualification 1981:								
Other	0.113	(0.047)	0.079	(0.074)	0.142	(0.049)	0.095	(0.074)
O Level	0.052	(0.037)	-0.021	(0.041)	0.125	(0.047)	0.008	(0.046)
Lower Vocational	0.156	(0.045)	-0.008	(0.047)	0.250	(0.059)	0.037	(0.058)
5 + O Levels	0.210	(0.040)	0.038	(0.043)	0.318	(0.060)	0.084	(0.057)
Middle Vocational	0.217	(0.046)	0.020	(0.046)	0.334	(0.069)	0.072	(0.062)
A Levels	0.406	(0.051)	0.070	(0.053)	0.521	(0.072)	0.122	(0.066)
Upper Vocational	0.480	(0.048)	0.056	(0.053)	0.616	(0.090)	0.129	(0.084)
Degree	0.714	(0.048)	0.038	(0.072)	0.896	(0.100)	0.139	(0.107)
Experience	0.039	(0.005)	0.059	(0.007)	0.040	(0.005)	0.057	(0.007)
Experience 1981			-0.080	(0.013)			-0.074	(0.013)
λ_q					-0.071	(0.027)	-0.040	(0.024)
λ_{eptc}					-0.012	(0.024)	0.007	(0.029)
λ_{qtc}					-0.096	(0.038)	-0.054	(0.039)
Number of observations	1002		1002		1002		1002	
P-value regional dummies	0.000		0.000		0.000		0.000	
P-value ability dummies	0.032				0.689			
Log Likelihood	-288.79		-393.97		-278.79		-390.62	
R^2	0.4910		0.2436		0.5011		0.2486	

very interesting because they indicate the extent to which training received is firm specific or is transportable. The coefficients are generally positive but are only significant for on-the-job training. This suggests that on-the-job EPTCs are relatively portable, whereas off-the job employer provided training for males in this cohort are relatively (though not entirely) firm specific.

For QTCs undertaken between 1981 and 1991 it is only middle and upper vocational qualifications and degree QTCs that have a positive impact on wages. Again it is important to control for correlated transitory effects and estimates which do not do this underestimate the returns to such training. Education and training received prior to 1981 appears more important than QTCs undertaken after 1981, with all types of qualification having a positive impact on wage levels. Again our IV estimates are well above our OLS estimates of the returns to such qualifications, but it is clear that the returns are less than those suggested in the previous Table when no account was taken of work related training. The return to a degree for men is substantially reduced and suggests a return of around 70 per cent rather than 95 per cent, compared to individuals with no qualifications. Higher qualifications also appear to have an impact on wage growth over the period 1981 to 1991. Individuals whose highest qualification was A levels in 1981, have wage growth which is 20 per cent higher than non-qualified individuals over the same period. We also see that an EPTC undertaken in the person's 1981 job and first job have a significant effect on the level of the 1991 wage, although not on wage growth over the 10 years to 1991. This suggests that such training only has an impact on the level of the wage and not on subsequent growth.

In Table 6.6 we present the results for women. Here, unlike for men we find that productivity shocks are not important in estimating the returns to employer provided training courses. Once again it would appear that both of the methods we use to control for unobserved permanent individual effects give reasonably similar results. For women, as for men, the largest impact on wages comes from EPTCs undertaken with their current employer, and once again it is off-the-job EPTCs which have the biggest impact. Training obtained with the previous employer, has a positive, though generally insignificant, effect suggesting that EPTCs may be less portable for women. The overall magnitude of the effects are not significantly different than those obtained for men.

Private and Government training courses also appear to have a significant and positive effect on women's wages, something that was not true for men. For women, as for men, most qualification training courses also have a positive impact on wages, particularly upper vocational and degree courses. Once again our IV estimates of the returns to these courses are above our OLS estimates.

For women, employer provided training received prior to 1981 has no affect on 1991 wages (unlike for men). As for men, school qualifications have a significant effect on 1991 wages and the higher the qualification, the higher the return. Once again, the estimates of these returns are significantly less than those obtained when no account was taken of work related training. However, unlike for men, there is only very weak evidence that formal qualifications such as O levels, A levels, Upper Vocational or Degree qualifications obtained prior to 1981 have a positive impact on wage growth over the 10 years to 1991.

6.4.5 Does the timing of training matter?

In the results presented so far, we have assumed that work related training only affects the level and not the growth of wages. If, however, it affects both the level and the rate of growth of wages, then earlier training should have a larger impact than later training. If, on the other hand, training affects the level of wages only temporarily and as training skills depreciate, wages return to their old path, then we might expect more recent training to impact on

Table 6.7: Timing and Male Returns to Training

Variable	Recent Courses Coef.	(S.E.)	Distant Courses Coef.	(S.E.)	P-value for F test of equality
WRTCs since 1981:					
Current Job:					
On–the–job EPTC(s)	0.046	(0.028)	-0.004	(0.028)	0.174
Off–the–job EPTC(s)	0.084	(0.028)	0.064	(0.030)	0.614
Previous Job:					
On–the–job EPTC(s)	-0.101	(0.055)	0.184	(0.040)	0.000
Off–the–job EPTC(s)	-0.177	(0.059)	0.051	(0.041)	0.001
Highest QTC since 1981:					
Other	0.023	(0.071)	-0.053	(0.055)	0.242
Lower Vocational	0.049	(0.086)	0.121	(0.064)	0.345
Middle Vocational	0.001	(0.127)	0.210	(0.086)	0.119
Upper Vocational	0.283	(0.089)	0.272	(0.074)	0.871
Degree	0.626	(0.199)	0.261	(0.104)	0.048
Number of observations	1453				
P-value regional dummies	0.000				
P-value ability dummies	0.5168				
Log Likelihood	-430.83				
R^2	0.3887				

wages more than more distant training courses. We look at this issue in this section by separately identifying training courses commenced prior to 1989 from those commenced after 1989. The results of doing this are presented in Table 6.7 for men and Table 6.8 for women[9].

For men the evidence is mixed though it generally supports the hypothesis that timing does not matter. The timing of off-the-job employer provided training courses does not seem important as does the timing of most qualification courses. For the other types of EPTCs the estimates are too imprecise to make definitive conclusions. For women, timing seems a lot less important, though there is evidence that upper vocational qualifications undertaken since 1981 may affect both the level and growth of wages for women.

[9]In earlier versions of this work we experimented with the timing of this break, but this generally made little difference to the results obtained.

Table 6.8: Timing and Female Returns to Training

Variable	Recent Courses Coef.	(S.E.)	Distant Courses Coef.	(S.E.)	P-value for F test of equality
WRTCs since 1981:					
Current Job:					
On-the-job EPTC(s)	0.044	(0.036)	0.038	(0.034)	0.891
Off-the-job EPTC(s)	0.096	(0.038)	0.100	(0.045)	0.940
Previous Job:					
On-the-job EPTC(s)	0.041	(0.066)	0.015	(0.048)	0.750
Off-the-job EPTC(s)	-0.058	(0.068)	-0.015	(0.052)	0.632
Highest QTC since 1981:					
Other	0.112	(0.106)	0.174	(0.101)	0.645
Lower Vocational	0.077	(0.081)	-0.010	(0.068)	0.230
Middle Vocational	0.215	(0.147)	0.230	(0.084)	0.917
Upper Vocational	0.129	(0.099)	0.339	(0.080)	0.004
Degree	0.543	(0.232)	0.296	(0.119)	0.253
Number of observations	1002				
P-value regional dummies	0.000				
P-value ability dummies	0.6144				
Log Likelihood	-274.35				
R^2	0.5055				

6.4.6 Promotion and the Returns to Employer Provided Training

The returns to employer provided training, especially off-the-job training in the person's current job, would appear to be quite substantial. Are we just picking up the effects of other labour market phenomenon which are strongly correlated with the receipt of employer provided training or is this type of training providing a real return? For instance are our estimates just picking up the fact that people who receive this type of training are much more likely to have been promoted in their current job? The problem of including promotion variables in our wage equations, of course, is that they are also highly endogenous.

It is clear from the raw data that people who have received employer provided training in their current job are much more likely to have been promoted in their current job. For individuals who have received employer provided training in their current job, 64 per cent have been promoted in their current job, compared to only 28 per cent of people who have not received employer provided training in their current job.

In Table 6.9 we have re-estimated specifications (iii) and (iv) for both men and women and included a dummy variable identifying whether the individual has been promoted in their current job. Columns 1 and 3 give the results already reported in Tables 6.5 and 6.6 for specifications (iii) and (iv) respectively, whereas columns 2 and 4 show how these estimates are changed by including a promotion variable. Because of endogeneity problems, the estimated coefficient on the promotion variable is biased. However, it is reassuring to find that when we include these variables, the returns to employer provided training in the person's current job, although slightly smaller, are still positive and significant in all the cases where they were before[10].

6.4.7 Allowing for interactions with formal educational qualifications

As mentioned earlier, the returns to training may also differ depending on the amount of formal education a person has received. The estimates presented so far have not allowed for this possibility. To explore this issue we estimate separate wage equations for people with low qualifications in 1981 (None, Other or O Levels), for people with middle qualifications in 1981 (Low Vocational, 5+ O Levels, or Middle Vocational), and for people with high qualifications (A Levels, High Vocational or a Degree) by 1981. Summary statistics for these different qualification groups are given in Tables 6.16, 6.17 and 6.18 in Appendix A.6.4. The results of doing this for men are given in Table 6.10 and for women in Table 6.11. The tables only report results for specification (iii) which is the levels specification in which both types of endogeneity bias have been corrected for. The results show that employer provided training has the largest impact on the wages of more highly edu-

[10]This is also true if we also include a variable measuring tenure in the person's current job as well as promotion (see Blundell, Dearden and Meghir [31]) By including tenure, however, we reduce our sample size and it is for this reason that we have not reported the results here.

Table 6.9: Effect of Promotion on Training Returns

Variable	Males – Specification (iii)				Females – Specification (iii)			
	Coef.	(S.E.)	Coef.	(S.E.)	Coef.	(S.E.)	Coef.	(S.E)
Constant	1.194	(0.132)	1.188	(0.130)	0.462	(0.095)	0.509	(0.095)
Promoted current job			0.096	(0.019)			0.111	(0.025)
WRTCs since 1981:								
Current Job:								
On–the–job EPTC(s)	0.083	(0.027)	0.070	(0.026)	0.090	(0.036)	0.082	(0.036)
Off–the–job EPTC(s)	0.159	(0.026)	0.145	(0.026)	0.121	(0.036)	0.104	(0.036)
Previous Job:								
On–the–job EPTC(s)	0.136	(0.042)	0.138	(0.042)	0.052	(0.046)	0.071	(0.046)
Off–the–job EPTC(s)	0.047	(0.040)	0.055	(0.040)	0.031	(0.048)	0.048	(0.049)
PTC(s)	-0.016	(0.038)	-0.016	(0.038)	0.108	(0.040)	0.098	(0.040)
GTC(s)	-0.167	(0.074)	-0.167	(0.071)	0.105	(0.090)	0.121	(0.090)
> 3 WRTCs	0.092	(0.025)	0.092	(0.025)	0.063	(0.031)	0.056	(0.031)
Only one job since 1981	0.000	(0.019)	-0.025	(0.019)	0.120	(0.026)	0.084	(0.027)
Highest QTC since 1981:								
Other	-0.034	(0.052)	-0.039	(0.052)	0.146	(0.081)	0.149	(0.080)
Lower Vocational	0.106	(0.062)	0.095	(0.062)	0.028	(0.065)	0.027	(0.063)
Middle Vocational	0.180	(0.081)	0.181	(0.081)	0.231	(0.082)	0.218	(0.081)
Upper Vocational	0.270	(0.073)	0.256	(0.073)	0.318	(0.079)	0.299	(0.078)
Degree	0.277	(0.104)	0.273	(0.105)	0.342	(0.118)	0.319	(0.118)
More than one QTC	0.024	(0.031)	0.020	(0.031)	0.061	(0.042)	0.047	(0.042)
WRTCs by 1981:								
EPTC in 1981 job	0.045	(0.021)	0.043	(0.021)	-0.010	(0.024)	-0.013	(0.023)
EPTC in first job	0.039	(0.021)	0.040	(0.021)	-0.045	(0.027)	-0.046	(0.027)
Highest Qualification 1981:								
Other	0.100	(0.046)	0.095	(0.046)	0.142	(0.049)	0.144	(0.049)
O Level	0.176	(0.040)	0.175	(0.040)	0.125	(0.047)	0.119	(0.046)
Lower Vocational	0.207	(0.043)	0.212	(0.043)	0.250	(0.059)	0.255	(0.058)
5 + O Levels	0.236	(0.052)	0.230	(0.052)	0.318	(0.060)	0.303	(0.059)
Middle Vocational	0.292	(0.054)	0.290	(0.053)	0.334	(0.069)	0.323	(0.069)
A Levels	0.418	(0.070)	0.406	(0.070)	0.521	(0.072)	0.492	(0.070)
Upper Vocational	0.419	(0.074)	0.409	(0.073)	0.616	(0.090)	0.608	(0.088)
Degree	0.689	(0.095)	0.670	(0.093)	0.896	(0.100)	0.877	(0.098)
Experience	0.012	(0.008)	0.010	(0.008)	0.040	(0.005)	0.036	(0.005)
λ_q	-0.086	(0.024)	-0.086	(0.024)	-0.071	(0.027)	-0.072	(0.026)
λ_{eptc}	-0.051	(0.018)	-0.051	(0.018)	-0.012	(0.024)	-0.016	(0.024)
λ_{qtc}	-0.072	(0.035)	-0.068	(0.036)	-0.096	(0.038)	-0.089	(0.037)
Number of observations	1453		1453		1002		1002	
P-value regional dummies	0.000		0.000		0.000		0.000	
P-value ability dummies	0.654		0.663		0.689		0.720	
Log Likelihood	-438.83		-426.40		-278.79		-268.47	
R^2	0.3819		0.3924		0.5011		0.5112	

cated men and has very little impact on men with low qualifications. For women employer provided training has the largest impact on women with middle qualifications.

The returns to qualification training courses also vary for the different education groups. Most vocational qualifications have a positive significant effect on the wages of men with low education levels and this is also true for women. Degree qualifications are only significant for men who already possessed high education levels and they are significant for women with middle and high education levels. Upper vocational qualifications are also important for these groups.

6.5 Training and Gender Wage Differentials

In Table 6.12 we look at the observed gender wage for individuals by these same qualification groups. We see that the overall observed difference in the wages received by men and women is around 27 per cent which is less than that observed for the sample in the previous Chapter. Again most of these observed differences (for different qualification groups and the entire sample) appear to arise because of differences in the price paid for observed characteristics rather than differences in observed characteristics. It is also clear that differences in the training experience of men and women are the most important component of the observed differences in background for this sample. Once again observed gender wage differentials decrease with qualification. For low educated people, differences in the average characteristics of men and women explains almost none of the observed wage differential. This becomes less true for more educated groups. Differences in the returns to training for men and women play no role in explaining gender wage differentials.

Table 6.10: The Returns for Males by Highest Qualification

Variable	Low Quals		Middle Quals		High Quals	
	Coef.	(S.E.)	Coef.	(S.E.)	Coef.	(S.E.)
Constant	1.068	(0.236)	1.403	(0.229)	1.739	(0.204)
WRTCs since 1981:						
Current Job:						
On–the–job EPTC(s)	0.005	(0.055)	0.128	(0.042)	0.073	(0.042)
Off–the–job EPTC(s)	0.033	(0.056)	0.194	(0.040)	0.203	(0.041)
Previous Job:						
On–the–job EPTC(s)	0.097	(0.088)	0.060	(0.066)	0.171	(0.066)
Off–the–job EPTC(s)	0.053	(0.105)	0.067	(0.057)	0.013	(0.056)
PTC(s)	-0.090	(0.071)	-0.024	(0.061)	0.060	(0.059)
GTC(s)	-0.025	(0.122)	-0.248	(0.112)	-0.199	(0.167)
> 3 WRTCs	0.285	(0.048)	0.048	(0.038)	0.023	(0.042)
Only one job since 1981	0.039	(0.031)	-0.001	(0.031)	-0.073	(0.038)
Highest QTC since 1981:						
Other	-0.101	(0.114)	-0.126	(0.088)	0.011	(0.087)
Lower Vocational	0.114	(0.118)	-0.049	(0.110)	0.118	(0.096)
Middle Vocational	0.220	(0.142)	0.147	(0.121)	-0.067	(0.154)
Upper Vocational	0.270	(0.148)	0.109	(0.131)	0.290	(0.110)
Degree			0.071	(0.197)	0.296	(0.162)
More than one QTC	0.012	(0.061)	0.083	(0.051)	-0.025	(0.051)
WRTCs by 1981:						
EPTC in 1981 job	0.059	(0.036)	0.037	(0.034)	0.060	(0.043)
EPTC in first job	0.008	(0.031)	0.049	(0.032)	0.064	(0.050)
Highest Qualification 1981:						
Other	0.046	(0.056)				
O Level	0.137	(0.053)				
Lower Vocational						
5 + O Levels			0.045	(0.043)		
Middle Vocational			0.111	(0.041)		
A Levels						
Upper Vocational					-0.020	(0.049)
Degree					0.185	(0.071)
Experience	0.025	(0.015)	0.014	(0.013)	-0.002	(0.013)
λ_q	-0.032	(0.047)	-0.134	(0.040)	-0.069	(0.040)
λ_{eptc}	-0.009	(0.035)	-0.058	(0.031)	-0.062	(0.029)
λ_{qtc}	-0.056	(0.069)	0.002	(0.063)	-0.086	(0.059)
Number of observations	476		550		427	
P-value regional dummies	0.000		0.000		0.000	
P-value ability dummies	0.936		0.342		0.023	
Log Likelihood	-118.74		-144.74		-124.23	
R^2	0.3184		0.3107		0.3215	

Table 6.11: The Returns for Females by Highest Qualification

Variable	Low Quals		Middle Quals		High Quals	
	Coef.	(S.E.)	Coef.	(S.E.)	Coef.	(S.E.)
Constant	0.310	(0.144)	0.588	(0.171)	1.342	(0.190)
WRTCs since 1981:						
Current Job:						
On–the–job EPTC(s)	0.093	(0.070)	0.132	(0.071)	0.038	(0.049)
Off–the–job EPTC(s)	0.073	(0.061)	0.250	(0.063)	0.079	(0.051)
Previous Job:						
On–the–job EPTC(s)	0.019	(0.099)	0.186	(0.069)	0.011	(0.061)
Off–the–job EPTC(s)	0.116	(0.143)	0.139	(0.092)	-0.013	(0.059)
PTC(s)	0.082	(0.081)	0.316	(0.065)	0.098	(0.054)
GTC(s)	-0.022	(0.119)	-0.055	(0.130)	0.298	(0.126)
> 3 WRTCs	0.115	(0.054)	0.049	(0.058)	0.056	(0.042)
Only one job since 1981	0.097	(0.041)	0.147	(0.049)	0.117	(0.046)
Highest QTC since 1981:						
Other	0.288	(0.131)	0.021	(0.139)	0.065	(0.147)
Lower Vocational	0.194	(0.106)	-0.134	(0.096)	-0.076	(0.130)
Middle Vocational	0.450	(0.158)	-0.027	(0.129)	0.112	(0.154)
Upper Vocational	0.476	(0.152)	0.175	(0.129)	0.350	(0.128)
Degree			0.547	(0.299)	0.310	(0.182)
More than one QTC	0.007	(0.088)	0.102	(0.094)	0.084	(0.052)
WRTCs by 1981:						
EPTC in 1981 job	0.028	(0.036)	0.010	(0.043)	-0.025	(0.044)
EPTC in first job	-0.029	(0.042)	0.009	(0.043)	-0.125	(0.051)
Highest Qualification 1981:						
Other	0.091	(0.054)				
O Level	0.123	(0.064)				
Lower Vocational						
5 + O Levels			0.085	(0.049)		
Middle Vocational			0.107	(0.053)		
A Levels						
Upper Vocational					0.071	(0.069)
Degree					0.268	(0.087)
Experience	0.049	(0.007)	0.047	(0.009)	0.018	(0.011)
λ_q	-0.085	(0.045)	-0.076	(0.036)	-0.036	(0.044)
λ_{eptc}	0.029	(0.042)	-0.078	(0.046)	-0.021	(0.036)
λ_{qtc}	-0.136	(0.067)	-0.013	(0.052)	-0.104	(0.065)
Number of observations	423		259		320	
P-value regional dummies	0.001		0.000		0.000	
P-value ability dummies	0.719		0.191		0.507	
Log Likelihood	-105.31		-34.56		-87.98	
R^2	0.3892		0.4362		0.2879	

Table 6.12: Gender Wage Differentials by Education Qualification

Decomposition	Low Qualifications Est.	(S.E.)	Middle Qualifications Est.	(S.E.)	High Qualifications Est.	(S.E.)	All Persons Est.	(S.E.)
$(\overline{x}_m - \overline{x}_f)'\widehat{\beta}_m$:								
All Vars	0.015	(0.013)	0.052	(0.018)	0.056	(0.011)	0.053	(0.012)
Non-training Vars	-0.008	(0.013)	0.016	(0.017)	0.024	(0.010)	0.019	(0.012)
$\overline{x}'_f(\widehat{\beta}_m - \widehat{\beta}_f)$:								
All coefs	0.271	(0.038)	0.213	(0.030)	0.141	(0.043)	0.214	(0.018)
Non-training coefs	0.275	(0.043)	0.206	(0.045)	0.143	(0.071)	0.215	(0.038)
$\widehat{g}$	0.286	(0.035)	0.265	(0.023)	0.197	(0.042)	0.267	(0.013)

6.6 Conclusions

In this Chapter we have looked at the determinants and effects of different types of education and training. We find that men have a substantially higher probability of receiving both employer provided and qualification training courses between 1981 and 1991 than women in our sample. We also find that people who had received employer provided training before 1981 were more likely to receive employer provided training and undertake qualification training courses between 1981 and 1991.

For men, other factors which increased the probability of receiving employer provided training between 1981 and 1991 were to be married, in a high occupational social class, with a large employer and to be a member of a union in their 1981 job. For women the probability of receiving such training increased if they were in a high occupational social class, with a large employer and a union member in their 1981 job. Factors which increased the probability of men undertaking a qualification training course between 1981 and 1991 were to be in a public sector firm, a high occupational social class, a union member and to have relatively short tenure in their 1981 job. For females factors which increased this likelihood were to be in a public sector firm, in a high occupational social class, and a large employer in their 1981 job. All these findings are broadly consistent with previous research on the determinants of training.

We looked in detail how if participation in training is correlated with unobservable individual characteristics then estimates of the returns to training which do not take this into account will be biased. We discussed a number of alternative ways of eliminating correlation between participation in training and unobservables. These methods allowed us to take account of permanent unobservables such as individual differences in ability as well as transitory shocks to individual productivity which may be correlated with participation in different types of education and training and hence bias our estimates of the returns to education and training. Controlling for transitory productivity shocks turns out to be very important in estimating the returns to employer provided training for men, while controlling correlated transitory shocks turned out to be very important in estimating the returns to education and qualification training courses for both men and women. Both methods of controlling for correlated training effects gave broadly similar results.

The results of the study show that work related training, particularly on- and off-the-job employer provided training, significantly increases the earnings potential of both men and women. In particular it is very important for the wage outcomes of more educated men and middle educated women. Qualification training courses also generally confer significant wage differentials though this again varies by education level. For less educated men and women, vocational qualifications tend to be most important form of training.

What the Chapter also shows in that estimates of the returns to education, which do not take into account work related training will over-estimate the returns to such education. We also see that differences in the observed wages of men and women can be partly explained by differences in the amount of work related training received. However, most of the differential appears to be related to the fact that women are paid less for given characteristics than men. The extent to which this occurs tends to decline with education.

Appendices

A.6.1 Summary Statistics

Table 6.13: Summary Statistics

Variable	Males		Females	
	1932 Observations		1002 Observations	
	Mean	(Std Dev.)	Mean	(Std Dev.)
w_{2i}	1.636	(0.416)	1.370	(0.453)
w_{21}	1.169	(0.305)	1.009	(0.312)
Δw_{2i}	0.467	(0.422)	0.360	(0.412)
WRTCs since 1981:				
On–the–job EPTC(s) Current job	0.231	(0.421)	0.179	(0.383)
Off–the–job EPTC(s) Current job	0.255	(0.436)	0.170	(0.376)
On–the–job EPTC(s) Previous job	0.053	(0.224)	0.071	(0.257)
Off–the–job EPTC(s) Previous job	0.089	(0.286)	0.065	(0.246)
EPTC(s)	0.482	(0.500)	0.380	(0.486)
PTC(s)	0.057	(0.232)	0.049	(0.216)
GTC(s)	0.019	(0.135)	0.010	(0.099)
>3 WRTCs	0.225	(0.418)	0.153	(0.360)
Only one job since 1981	0.398	(0.490)	0.293	(0.456)
Highest QTC since 1981:				
None	0.688	(0.463)	0.726	(0.446)
Other	0.078	(0.268)	0.047	(0.212)
Lower Vocational	0.078	(0.269)	0.082	(0.274)
Middle Vocational	0.026	(0.160)	0.024	(0.153)
Upper Vocational	0.096	(0.294)	0.100	(0.300)
Degree	0.034	(0.181)	0.022	(0.147)
More than one QTC	0.111	(0.314)	0.089	(0.285)
Experience	15.794	(2.084)	14.449	(2.631)
WRTCs by 1981:				
EPTC in 1981 job	0.572	(0.495)	0.425	(0.495)
EPTC in first job	0.298	(0.458)	0.196	(0.397)
Highest Qualification 1981:				
None	0.173	(0.378)	0.171	(0.376)
Other	0.045	(0.208)	0.041	(0.198)
O Level	0.109	(0.312)	0.211	(0.408)
Lower Vocational	0.105	(0.307)	0.066	(0.248)
5 + O Levels	0.081	(0.273)	0.121	(0.326)
Middle Vocational	0.192	(0.394)	0.072	(0.258)
A Levels	0.072	(0.259)	0.063	(0.243)
Upper Vocational	0.106	(0.308)	0.135	(0.342)
Degree	0.116	(0.320)	0.122	(0.327)
One job only 1981	0.380	(0.486)	0.331	(0.471)
No. of children 1981	0.156	(0.435)	0.099	(0.365)
Married 1981	0.420	(0.494)	0.481	(0.500)
Private Sector 1981	0.666	(0.472)	0.542	(0.498)
Hours in 1981 job	41.801	(7.662)	36.460	(7.416)
Social Class 1981 job:				
Prof/Intermediate	0.249	(0.433)	0.312	(0.464)
Skilled non-manual	0.226	(0.418)	0.512	(0.500)
Skilled manual	0.398	(0.490)	0.059	(0.236)
Semi-skilled	0.109	(0.311)	0.107	(0.309)
Unskilled	0.018	(0.133)	0.010	(0.099)
Firm size 1981 job:				
$1--10$	0.131	(0.337)	0.164	(0.370)
$11--24$	0.122	(0.327)	0.164	(0.370)
$25--99$	0.242	(0.429)	0.236	(0.425)
$100-499$	0.234	(0.424)	0.231	(0.421)
500+	0.271	(0.445)	0.207	(0.405)
Union Member 1981	0.555	(0.497)	0.504	(0.500)
Years in 1981 job	3.685	(2.455)	3.325	(2.431)
Experience 1981	5.515	(1.938)	5.137	(2.033)

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Table 6.13 continued

Variable	Males		Females	
	1453 Observations		1002 Observations	
	Mean	(Std Dev.)	Mean	(Std Dev.)
Maths ability:				
1st quintile	0.148	(0.355)	0.155	(0.362)
2nd quintile	0.189	(0.392)	0.200	(0.400)
3rd quintile	0.209	(0.407)	0.206	(0.404)
4th quintile	0.209	(0.407)	0.231	(0.421)
5th quintile	0.244	(0.430)	0.210	(0.407)
Verbal ability:				
1st quintile	0.167	(0.373)	0.087	(0.282)
2nd quintile	0.213	(0.410)	0.154	(0.361)
3rd quintile	0.217	(0.412)	0.216	(0.411)
4th quintile	0.224	(0.417)	0.262	(0.440)
5th quintile	0.179	(0.383)	0.281	(0.450)
Teacher's rating:				
Avid reader	0.052	(0.221)	0.097	(0.296)
Above average reader	0.248	(0.432)	0.345	(0.476)
Average reader	0.454	(0.498)	0.458	(0.498)
Excellent number skills	0.052	(0.221)	0.031	(0.173)
Good number skills	0.215	(0.411)	0.211	(0.408)
Average number skills	0.453	(0.498)	0.492	(0.500)
Father's interest in edn:				
Very interested	0.307	(0.461)	0.329	(0.470)
Some interest	0.246	(0.431)	0.196	(0.397)
Mother's interest in edn:				
Very interested	0.422	(0.494)	0.507	(0.500)
Some interest	0.387	(0.487)	0.363	(0.481)
Father's years of education	9.452	(2.783)	9.390	(3.108)
No Father Figure	0.049	(0.216)	0.066	(0.248)
Mother's years of education	9.807	(1.919)	9.897	(1.957)
No Mother Figure	0.014	(0.119)	0.013	(0.113)
Father's social class 1974:				
Prof/Intermediate	0.241	(0.428)	0.258	(0.438)
Skilled non-manual	0.102	(0.303)	0.097	(0.296)
Skilled manual	0.396	(0.489)	0.392	(0.488)
Semi-skilled	0.134	(0.341)	0.099	(0.299)
Unskilled	0.028	(0.164)	0.038	(0.191)
Mother's social class 1974:				
Prof/Intermediate	0.119	(0.324)	0.119	(0.324)
Skilled non-manual	0.233	(0.423)	0.246	(0.431)
Skilled manual	0.047	(0.211)	0.047	(0.212)
Semi-skilled	0.217	(0.412)	0.227	(0.419)
Unskilled	0.072	(0.259)	0.071	(0.257)
Financial Difficulties 1974	0.100	(0.301)	0.098	(0.297)
Number of siblings	2.130	(1.667)	2.028	(1.544)
Number of older siblings	1.062	(1.346)	0.982	(1.152)
Brothers only	0.275	(0.446)	0.259	(0.439)
Sisters only	0.244	(0.430)	0.264	(0.441)

A.6.2 Training Participation

Table 6.14: Training Participation

Variable	EPTC Coef.	EPTC (S.E.)	QTC Coef.	QTC (S.E.)
Constant	-1.920	(0.451)		
WRTCs by 1981:				
EPTC in 1981 job	0.447	(0.060)	0.263	(0.059)
EPTC in first job	0.022	(0.075)	-0.052	(0.072)
One job only 1981	0.135	(0.081)	0.038	(0.078)
No. of children 1981	-0.113	(0.076)	0.037	(0.074)
Married 1981	0.048	(0.059)	-0.070	(0.058)
Private Sector 1981	-0.085	(0.064)	-0.303	(0.062)
Hours in 1981 job	0.002	(0.004)	0.002	(0.004)
Social Class 1981 job:				
Prof/Intermediate	0.903	(0.282)	0.663	(0.258)
Skilled non-manual	1.031	(0.281)	0.356	(0.257)
Skilled manual	0.376	(0.279)	0.237	(0.256)
Semi-skilled	0.544	(0.285)	0.012	(0.264)
Firm size 1981 job:				
11 – 24	0.195	(0.105)	-0.190	(0.102)
25 – 99	0.258	(0.094)	-0.153	(0.090)
100 – 499	0.251	(0.096)	0.010	(0.091)
500+	0.274	(0.097)	-0.004	(0.092)
Union Member 1981	0.210	(0.064)	-0.039	(0.063)
Years in 1981 job	-0.042	(0.020)	-0.064	(0.019)
Experience 1981	-0.007	(0.023)	-0.007	(0.022)
Maths ability:				
2nd quintile	-0.001	(0.097)	0.197	(0.098)
3rd quintile	0.081	(0.099)	0.068	(0.101)
4th quintile	0.117	(0.103)	0.128	(0.104)
5th quintile	0.167	(0.109)	0.104	(0.110)
Verbal ability:				
2nd quintile	-0.029	(0.108)	-0.004	(0.110)
3rd quintile	0.038	(0.117)	0.025	(0.118)
4th quintile	-0.030	(0.123)	0.108	(0.124)
5th quintile	-0.041	(0.132)	-0.012	(0.133)
Male	0.437	(0.066)	0.231	(0.064)
μ_1			1.061	(0.413)
μ_2			1.281	(0.413)
μ_3			1.616	(0.414)
μ_4			1.750	(0.414)
μ_5			2.630	(0.417)
Number of observations	2455		2455	
P-value Ability Variables	0.770		0.433	
P-value 1981 Regional Vars	0.434		0.543	
P-value 1974 Family Vars	0.898		0.001	
Log Likelihood	-1477.08		-2401.16	
(Pseudo) R^2	0.111		0.068	

A.6.3 Determinants of Highest Qualifications

Table 6.15: Determinants of Highest Qualifications

Variable	Males		Females		Persons	
	Coef.	(S.E.)	Coef.	(S.E.)	Coef.	(S.E.)
Maths ability:						
2nd quintile	0.188	(0.101)	0.249	(0.118)	0.219	(0.076)
3rd quintile	0.258	(0.103)	0.212	(0.122)	0.239	(0.078)
4th quintile	0.248	(0.108)	0.270	(0.125)	0.259	(0.081)
5th quintile	0.461	(0.113)	0.430	(0.134)	0.433	(0.086)
Verbal ability:						
2nd quintile	0.111	(0.101)	0.124	(0.161)	0.091	(0.085)
3rd quintile	0.126	(0.113)	0.189	(0.162)	0.130	(0.091)
4th quintile	0.329	(0.120)	0.360	(0.168)	0.309	(0.096)
5th quintile	0.337	(0.134)	0.465	(0.175)	0.374	(0.104)
Teacher's rating:						
Avid reader	0.350	(0.174)	1.107	(0.208)	0.717	(0.128)
Above average reader	0.304	(0.122)	0.685	(0.171)	0.445	(0.097)
Average reader	0.307	(0.097)	0.409	(0.148)	0.325	(0.079)
Excellent number skills	0.573	(0.159)	0.266	(0.234)	0.459	(0.129)
Good number skills	0.407	(0.107)	0.078	(0.126)	0.277	(0.080)
Average number skills	0.176	(0.084)	0.170	(0.095)	0.189	(0.062)
Father's interest in edn:						
Very interested	0.289	(0.090)	0.174	(0.100)	0.224	(0.066)
Some interest	0.067	(0.076)	-0.033	(0.097)	0.032	(0.059)
Mother's interest in edn:						
Very interested	0.050	(0.100)	0.053	(0.131)	0.071	(0.078)
Some interest	0.186	(0.086)	0.070	(0.120)	0.156	(0.069)
Father's years of education	0.090	(0.021)	0.080	(0.023)	0.081	(0.015)
No Father Figure	0.949	(0.266)	0.806	(0.311)	0.861	(0.199)
Mother's years of education	0.054	(0.025)	0.091	(0.027)	0.074	(0.018)
No Mother Figure	0.168	(0.343)	1.049	(0.395)	0.583	(0.256)
Father's social class 1974:						
Prof/Intermediate	0.431	(0.151)	0.192	(0.181)	0.327	(0.115)
Skilled non-manual	0.260	(0.161)	-0.038	(0.198)	0.154	(0.123)
Skilled manual	0.189	(0.140)	-0.089	(0.171)	0.058	(0.107)
Semi-skilled	-0.042	(0.154)	-0.135	(0.195)	-0.087	(0.119)
Unskilled	-0.226	(0.217)	-0.165	(0.237)	-0.189	(0.158)
Mother's social class 1974:						
Prof/Intermediate	-0.103	(0.101)	0.393	(0.125)	0.112	(0.078)
Skilled non-manual	-0.053	(0.081)	0.048	(0.098)	-0.017	(0.062)
Skilled manual	-0.206	(0.140)	0.158	(0.169)	-0.049	(0.107)
Semi-skilled	-0.036	(0.081)	-0.028	(0.099)	-0.029	(0.062)
Unskilled	-0.087	(0.117)	-0.077	(0.147)	-0.055	(0.090)
Financial Difficulties 1974	-0.134	(0.108)	-0.198	(0.131)	-0.158	(0.082)
Number of siblings	-0.061	(0.027)	-0.083	(0.032)	-0.073	(0.021)
Number of older siblings	-0.005	(0.031)	0.056	(0.040)	0.022	(0.024)
Brothers only	0.054	(0.071)	0.111	(0.088)	0.082	(0.055)
Sisters only	-0.037	(0.074)	0.116	(0.087)	0.026	(0.056)
Male					0.218	(0.046)
μ_1	1.328	(0.303)	1.826	(0.378)	1.638	(0.236)
μ_2	1.545	(0.303)	2.020	(0.378)	1.842	(0.236)
μ_3	1.960	(0.303)	2.797	(0.381)	2.397	(0.236)
μ_4	2.295	(0.304)	3.012	(0.382)	2.678	(0.237)
μ_5	2.541	(0.304)	3.412	(0.384)	2.976	(0.238)
μ_6	3.152	(0.307)	3.662	(0.385)	3.438	(0.239)
μ_7	3.422	(0.308)	3.890	(0.387)	3.686	(0.240)
μ_8	3.947	(0.311)	4.521	(0.391)	4.247	(0.243)
Number of observations	1453		1002		2455	
P-value regional dummies	0.076		0.076		0.027	
Log Likelihood	-2799.97		-1863.85		-4760.58	
(Pseudo) R^2	0.0914		0.1077		0.0907	

A.6.4 Summary Statistics by Highest Qualification

Table 6.16: Summary Statistics – Low Qualifications

Variable	Males		Females	
	476 Observations		423 Observations	
	Mean	(Std Dev.)	Mean	(Std Dev.)
w_{2i}	1.458	(0.377)	1.136	(0.398)
w_{21}	1.099	(0.315)	0.883	(0.320)
Δw_{2i}	0.359	(0.383)	0.253	(0.425)
WRTCs since 1981:				
Current Job:				
On–the–job EPTC(s)	0.210	(0.408)	0.135	(0.342)
Off–the–job EPTC(s)	0.143	(0.350)	0.102	(0.303)
Previous Job:				
On–the–job EPTC(s)	0.038	(0.191)	0.043	(0.202)
Off–the–job EPTC(s)	0.040	(0.196)	0.019	(0.136)
EPTC	0.351	(0.478)	0.253	(0.435)
PTC(s)	0.038	(0.191)	0.021	(0.144)
GTC(s)	0.019	(0.136)	0.012	(0.108)
>3 WRTCs	0.134	(0.341)	0.083	(0.276)
Only one job since 1981	0.445	(0.498)	0.298	(0.458)
Highest QTC since 1981:				
None	0.803	(0.399)	0.827	(0.378)
Other	0.059	(0.236)	0.043	(0.202)
Lower Vocational	0.095	(0.293)	0.076	(0.265)
Middle Vocational	0.017	(0.129)	0.026	(0.159)
Upper Vocational	0.027	(0.163)	0.028	(0.166)
Degree	0.000	(0.000)	0.000	(0.000)
More than one QTC	0.074	(0.261)	0.054	(0.227)
Experience	16.701	(1.162)	15.317	(2.413)
WRTCs by 1981:				
EPTC in 1981 job	0.410	(0.492)	0.340	(0.474)
EPTC in first job	0.290	(0.454)	0.191	(0.394)
Highest Qualification 1981:				
None	0.527	(0.500)	0.404	(0.491)
Other	0.139	(0.346)	0.097	(0.296)
O Level	0.334	(0.472)	0.499	(0.501)
One job only 1981	0.265	(0.442)	0.307	(0.462)
No. of children 1981	0.235	(0.522)	0.161	(0.470)
Married 1981	0.479	(0.500)	0.522	(0.500)
Private Sector 1981	0.691	(0.462)	0.761	(0.427)
Hours in 1981 job	43.032	(8.155)	36.116	(7.698)
Social Class 1981 job:				
Prof/Intermediate	0.099	(0.299)	0.095	(0.293)
Skilled non-manual	0.212	(0.409)	0.577	(0.495)
Skilled manual	0.429	(0.495)	0.087	(0.283)
Semi-skilled	0.216	(0.412)	0.227	(0.419)
Unskilled	0.044	(0.206)	0.014	(0.118)
Firm size 1981 job:				
1 – 10	0.155	(0.363)	0.213	(0.410)
11 – 24	0.153	(0.361)	0.118	(0.323)
25 – 99	0.200	(0.400)	0.251	(0.434)
100 – 499	0.258	(0.438)	0.222	(0.416)
500+	0.233	(0.423)	0.196	(0.398)
Union Member 1981	0.559	(0.497)	0.428	(0.495)
Years in 1981 job	4.071	(2.327)	4.092	(2.546)
Experience 1981	6.468	(0.745)	6.316	(1.007)

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Table 6.16 continued

Variable	Males 476 Observations Mean	(Std Dev.)	Females 423 Observations Mean	(Std Dev.)
Maths ability:				
1st quintile	0.239	(0.427)	0.232	(0.422)
2nd quintile	0.235	(0.425)	0.229	(0.421)
3rd quintile	0.200	(0.400)	0.217	(0.413)
4th quintile	0.197	(0.399)	0.201	(0.401)
5th quintile	0.128	(0.335)	0.121	(0.326)
Verbal ability:				
1st quintile	0.282	(0.450)	0.156	(0.363)
2nd quintile	0.269	(0.444)	0.225	(0.418)
3rd quintile	0.200	(0.400)	0.253	(0.435)
4th quintile	0.145	(0.352)	0.215	(0.411)
5th quintile	0.105	(0.307)	0.151	(0.359)
Teacher's rating:				
Avid reader	0.023	(0.150)	0.026	(0.159)
Above average reader	0.158	(0.365)	0.234	(0.424)
Average reader	0.387	(0.487)	0.556	(0.497)
Excellent number skills	0.027	(0.163)	0.009	(0.097)
Good number skills	0.109	(0.312)	0.139	(0.347)
Average number skills	0.391	(0.488)	0.463	(0.499)
Father's interest in edn:				
Very interested	0.189	(0.392)	0.191	(0.394)
Some interest	0.231	(0.422)	0.227	(0.419)
Mother's interest in edn:				
Very interested	0.313	(0.464)	0.366	(0.482)
Some interest	0.403	(0.491)	0.437	(0.497)
Father's years of education	8.910	(2.482)	8.863	(2.543)
No Father Figure	0.059	(0.236)	0.064	(0.245)
Mother's years of education	9.458	(1.693)	9.447	(1.393)
No Mother Figure	0.019	(0.136)	0.012	(0.108)
Father's social class 1974:				
Prof/Intermediate	0.124	(0.330)	0.135	(0.342)
Skilled non-manual	0.086	(0.281)	0.076	(0.265)
Skilled manual	0.418	(0.494)	0.470	(0.500)
Semi-skilled	0.189	(0.392)	0.135	(0.342)
Unskilled	0.048	(0.215)	0.054	(0.227)
Mother's social class 1974:				
Prof/Intermediate	0.090	(0.287)	0.047	(0.212)
Skilled non-manual	0.197	(0.399)	0.227	(0.419)
Skilled manual	0.057	(0.232)	0.045	(0.207)
Semi-skilled	0.244	(0.430)	0.279	(0.449)
Unskilled	0.069	(0.254)	0.095	(0.293)
Financial Difficulties 1974	0.164	(0.371)	0.142	(0.349)
Number of siblings	2.544	(1.991)	2.317	(1.770)
Number of older siblings	1.324	(1.630)	1.116	(1.254)
Brothers only	0.221	(0.415)	0.227	(0.419)
Sisters only	0.221	(0.415)	0.222	(0.416)

Table 6.17: Summary Statistics - Middle Qualifications

Variable	Males		Females	
	550 Observations		259 Observations	
	Mean	(Std Dev.)	Mean	(Std Dev.)
w_{2i}	1.606	(0.380)	1.347	(0.369)
w_{21}	1.203	(0.289)	1.007	(0.250)
Δw_{2i}	0.403	(0.394)	0.340	(0.334)
WRTCs since 1981:				
Current Job:				
On–the–job EPTC(s)	0.229	(0.421)	0.220	(0.415)
Off–the–job EPTC(s)	0.262	(0.440)	0.178	(0.383)
Previous Job:				
On–the–job EPTC(s)	0.047	(0.212)	0.081	(0.273)
Off–the–job EPTC(s)	0.080	(0.272)	0.062	(0.241)
EPTC	0.465	(0.499)	0.440	(0.497)
PTC(s)	0.062	(0.241)	0.027	(0.162)
GTC(s)	0.018	(0.134)	0.004	(0.062)
>3 WRTCs	0.218	(0.413)	0.162	(0.369)
Only one job since 1981	0.400	(0.490)	0.355	(0.480)
Highest QTC since 1981:				
None	0.696	(0.460)	0.757	(0.430)
Other	0.089	(0.285)	0.054	(0.227)
Lower Vocational	0.084	(0.277)	0.108	(0.311)
Middle Vocational	0.038	(0.192)	0.035	(0.183)
Upper Vocational	0.082	(0.274)	0.039	(0.193)
Degree	0.011	(0.104)	0.008	(0.088)
More than one QTC	0.124	(0.329)	0.093	(0.291)
Experience	16.545	(1.278)	14.958	(2.133)
WRTCs by 1981:				
EPTC in 1981 job	0.631	(0.483)	0.471	(0.500)
EPTC in first job	0.395	(0.489)	0.236	(0.425)
Highest Qualification 1981:				
Lower Vocational	0.278	(0.449)	0.255	(0.437)
5 + O Levels	0.215	(0.411)	0.467	(0.500)
Middle Vocational	0.507	(0.500)	0.278	(0.449)
One job only 1981	0.387	(0.488)	0.313	(0.465)
No. of children 1981	0.165	(0.448)	0.069	(0.310)
Married 1981	0.435	(0.496)	0.529	(0.500)
Private Sector 1981	0.696	(0.460)	0.525	(0.500)
Hours in 1981 job	42.802	(7.582)	37.035	(6.304)
Social Class 1981 job:				
Prof/Intermediate	0.147	(0.355)	0.135	(0.343)
Skilled non-manual	0.187	(0.390)	0.749	(0.434)
Skilled manual	0.582	(0.494)	0.062	(0.241)
Semi-skilled	0.076	(0.266)	0.039	(0.193)
Unskilled	0.007	(0.085)	0.015	(0.124)
Firm size 1981 job:				
1 – 10	0.125	(0.332)	0.166	(0.373)
11 – 24	0.111	(0.314)	0.185	(0.389)
25 – 99	0.255	(0.436)	0.208	(0.407)
100 – 499	0.233	(0.423)	0.243	(0.430)
500+	0.276	(0.448)	0.197	(0.398)
Union Member 1981	0.618	(0.486)	0.490	(0.501)
Years in 1981 job	4.123	(2.552)	3.666	(2.273)
Experience 1981	6.239	(1.059)	5.612	(1.177)

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Table 6.17 continued

Variable	Males 550 Observations Mean	(Std Dev.)	Females 259 Observations Mean	(Std Dev.)
Maths ability:				
1st quintile	0.125	(0.332)	0.135	(0.343)
2nd quintile	0.205	(0.404)	0.208	(0.407)
3rd quintile	0.218	(0.413)	0.166	(0.373)
4th quintile	0.205	(0.404)	0.236	(0.425)
5th quintile	0.245	(0.431)	0.255	(0.437)
Verbal ability:				
1st quintile	0.165	(0.372)	0.039	(0.193)
2nd quintile	0.216	(0.412)	0.135	(0.343)
3rd quintile	0.240	(0.427)	0.228	(0.420)
4th quintile	0.229	(0.421)	0.293	(0.456)
5th quintile	0.149	(0.357)	0.305	(0.461)
Teacher's rating:				
Avid reader	0.040	(0.196)	0.089	(0.285)
Above average reader	0.222	(0.416)	0.417	(0.494)
Average reader	0.525	(0.500)	0.432	(0.496)
Excellent number skills	0.031	(0.173)	0.023	(0.151)
Good number skills	0.209	(0.407)	0.243	(0.430)
Average number skills	0.531	(0.499)	0.521	(0.501)
Father's interest in edn:				
Very interested	0.289	(0.454)	0.378	(0.486)
Some interest	0.273	(0.446)	0.166	(0.373)
Mother's interest in edn:				
Very interested	0.389	(0.488)	0.541	(0.499)
Some interest	0.425	(0.495)	0.367	(0.483)
Father's years of education	9.287	(2.447)	9.243	(3.004)
No Father Figure	0.044	(0.204)	0.073	(0.261)
Mother's years of education	9.642	(1.604)	9.757	(1.693)
No Mother Figure	0.013	(0.112)	0.012	(0.107)
Father's social class 1974:				
Prof/Intermediate	0.220	(0.415)	0.236	(0.425)
Skilled non-manual	0.096	(0.295)	0.108	(0.311)
Skilled manual	0.438	(0.497)	0.425	(0.495)
Semi-skilled	0.140	(0.347)	0.085	(0.279)
Unskilled	0.016	(0.127)	0.035	(0.183)
Mother's social class 1974:				
Prof/Intermediate	0.111	(0.314)	0.112	(0.316)
Skilled non-manual	0.236	(0.425)	0.263	(0.441)
Skilled manual	0.051	(0.220)	0.062	(0.241)
Semi-skilled	0.231	(0.422)	0.228	(0.420)
Unskilled	0.104	(0.305)	0.066	(0.248)
Financial Difficulties 1974	0.082	(0.274)	0.073	(0.261)
Number of siblings	2.040	(1.526)	1.861	(1.322)
Number of older siblings	1.044	(1.290)	0.931	(1.112)
Brothers only	0.293	(0.455)	0.266	(0.443)
Sisters only	0.247	(0.432)	0.290	(0.454)

Table 6.18: Summary Statistics – High Qualifications

Variable	Males		Females	
	427 Observations		320 Observations	
	Mean	(Std Dev.)	Mean	(Std Dev.)
w_{2i}	1.873	(0.393)	1.697	(0.378)
w_{21}	1.204	(0.301)	1.178	(0.263)
Δw_{2i}	0.669	(0.429)	0.519	(0.404)
WRTCs since 1981:				
Current Job:				
On–the–job EPTC(s)	0.255	(0.437)	0.203	(0.403)
Off–the–job EPTC(s)	0.370	(0.483)	0.253	(0.435)
Previous Job:				
On–the–job EPTC(s)	0.077	(0.267)	0.100	(0.300)
Off–the–job EPTC(s)	0.157	(0.364)	0.128	(0.335)
EPTC	0.649	(0.478)	0.500	(0.501)
PTC(s)	0.073	(0.260)	0.103	(0.305)
GTC(s)	0.019	(0.136)	0.013	(0.111)
>3 WRTCs	0.335	(0.473)	0.238	(0.426)
Only one job since 1981	0.344	(0.476)	0.238	(0.426)
Highest QTC since 1981:				
None	0.550	(0.498)	0.566	(0.496)
Other	0.084	(0.278)	0.047	(0.212)
Lower Vocational	0.054	(0.226)	0.069	(0.253)
Middle Vocational	0.021	(0.144)	0.013	(0.111)
Upper Vocational	0.190	(0.393)	0.244	(0.430)
Degree	0.101	(0.301)	0.063	(0.242)
More than one QTC	0.136	(0.343)	0.131	(0.338)
Experience	13.816	(2.371)	12.890	(2.584)
WRTCs by 1981:				
EPTC in 1981 job	0.677	(0.468)	0.500	(0.501)
EPTC in first job	0.183	(0.387)	0.169	(0.375)
Highest Qualification 1981:				
A Levels	0.246	(0.431)	0.197	(0.398)
Upper Vocational	0.361	(0.481)	0.422	(0.495)
Degree	0.393	(0.489)	0.381	(0.486)
One job only 1981	0.499	(0.501)	0.378	(0.486)
No. of children 1981	0.054	(0.255)	0.041	(0.198)
Married 1981	0.335	(0.473)	0.388	(0.488)
Private Sector 1981	0.600	(0.491)	0.266	(0.442)
Hours in 1981 job	39.141	(6.465)	36.450	(7.852)
Social Class 1981 job:				
Prof/Intermediate	0.548	(0.498)	0.744	(0.437)
Skilled non-manual	0.290	(0.454)	0.234	(0.424)
Skilled manual	0.129	(0.335)	0.019	(0.136)
Semi-skilled	0.030	(0.172)	0.003	(0.056)
Unskilled	0.002	(0.048)	0.000	(0.000)
Firm size 1981 job:				
1 – 10	0.110	(0.313)	0.097	(0.296)
11 – 24	0.101	(0.301)	0.206	(0.405)
25 – 99	0.274	(0.447)	0.238	(0.426)
100 – 499	0.208	(0.407)	0.231	(0.422)
500+	0.307	(0.462)	0.228	(0.420)
Union Member 1981	0.471	(0.500)	0.616	(0.487)
Years in 1981 job	2.689	(2.170)	2.035	(1.804)
Experience 1981	3.519	(2.248)	3.194	(2.165)

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Table 6.18 continued

Variable	Males 427 Observations Mean	(Std Dev.)	Females 320 Observations Mean	(Std Dev.)
Maths ability:				
1st quintile	0.075	(0.264)	0.069	(0.253)
2nd quintile	0.117	(0.322)	0.153	(0.361)
3rd quintile	0.208	(0.407)	0.222	(0.416)
4th quintile	0.227	(0.419)	0.266	(0.442)
5th quintile	0.372	(0.484)	0.291	(0.455)
Verbal ability:				
1st quintile	0.040	(0.196)	0.034	(0.182)
2nd quintile	0.148	(0.355)	0.075	(0.264)
3rd quintile	0.206	(0.405)	0.156	(0.364)
4th quintile	0.307	(0.462)	0.300	(0.459)
5th quintile	0.300	(0.459)	0.434	(0.496)
Teacher's rating:				
Avid reader	0.098	(0.298)	0.197	(0.398)
Above average reader	0.382	(0.486)	0.434	(0.496)
Average reader	0.438	(0.497)	0.350	(0.478)
Excellent number skills	0.105	(0.307)	0.066	(0.248)
Good number skills	0.342	(0.475)	0.278	(0.449)
Average number skills	0.422	(0.494)	0.506	(0.501)
Father's interest in edn:				
Very interested	0.461	(0.499)	0.472	(0.500)
Some interest	0.230	(0.421)	0.178	(0.383)
Mother's interest in edn:				
Very interested	0.585	(0.493)	0.666	(0.473)
Some interest	0.321	(0.467)	0.263	(0.441)
Father's years of education	10.269	(3.282)	10.206	(3.661)
No Father Figure	0.044	(0.206)	0.063	(0.242)
Mother's years of education	10.410	(2.346)	10.606	(2.518)
No Mother Figure	0.012	(0.108)	0.016	(0.124)
Father's social class 1974:				
Prof/Intermediate	0.398	(0.490)	0.441	(0.497)
Skilled non-manual	0.126	(0.333)	0.116	(0.320)
Skilled manual	0.319	(0.466)	0.263	(0.441)
Semi-skilled	0.066	(0.248)	0.063	(0.242)
Unskilled	0.019	(0.136)	0.019	(0.136)
Mother's social class 1974:				
Prof/Intermediate	0.162	(0.369)	0.219	(0.414)
Skilled non-manual	0.267	(0.443)	0.256	(0.437)
Skilled manual	0.030	(0.172)	0.038	(0.190)
Semi-skilled	0.169	(0.375)	0.156	(0.364)
Unskilled	0.035	(0.184)	0.044	(0.205)
Financial Difficulties 1974	0.054	(0.226)	0.059	(0.237)
Number of siblings	1.785	(1.315)	1.781	(1.316)
Number of older siblings	0.794	(0.962)	0.847	(1.019)
Brothers only	0.311	(0.464)	0.297	(0.458)
Sisters only	0.267	(0.443)	0.300	(0.459)

Chapter 7

Conclusions

This thesis has looked at the relationship between education, training and earnings in Australia and Britain using data from the Australian Longitudinal Survey (ALS), Australian Youth Survey (AYS) and British National Child Development Survey (NCDS). We find that education and training generally confer significant wage advantages on individuals, but the actual size of the estimated return depends crucially on the estimation procedure used. Education and training outcomes are endogenous and estimates that do not take this into account may over- or under- estimate the true returns to education and training. These biases arises because unobserved individual characteristics which determine wages, are also correlated with education and/or training. We generally find that OLS estimates of the returns to education and training, which assume that education and training are exogenous, are significantly less than those obtained from estimation procedures which treat education and/or training as endogenous. This, however, is not always true. Different estimation procedures make different assumptions about the underlying source of variation in observed education and training decisions and these assumptions can have important implications for the size of the estimates obtained.

There have been three main methods proposed in the economic literature for correcting for this endogeneity bias and all of these have been used in the thesis. These are instrumental variable techniques, proxy methods and fixed effect estimation techniques. Generally researchers, because of data constraints, have chosen one of these techniques in order to obtain corrected estimates of the returns to education and/or training. The data used in this thesis allowed us to directly compare estimates of the returns to education and training using a number of these econometric techniques on a common sample. We find that some of the different methods which have been devised for controlling for correlated individual effects can produce very different estimates of the returns to education on the same sample of individuals. Other methods seem to be much more closely related.

In Chapter 3 we looked at the early returns to formal educational outcomes in Australia using both the ALS and AYS data. The Chapter used instrumental variable techniques to deal with the endogeneity of education. We argued that an individual's position in the family in terms of how many older siblings they have is a crucial factor in determining educational outcomes in Australia, controlling for family size and year of birth. We show that individuals with more older siblings, have significantly less education than individuals from similarly sized families with less older siblings. Moreover, an individual's birth order is exogenous given family size. We assume that the number of older siblings, has no legitimate role in a wage equation, controlling for education and family size. We therefore exploit this exogenous influence on the education decision and use the number of older siblings as an instrument for education in various wage equations which estimate the returns to education. We also use other family characteristics and school variables as instruments. We find that conventional OLS estimates of the returns to education are generally significantly lower than instrumental variable estimators which account for the endogeneity of education, especially for women. There is some question as to the robustness of our Male estimates of the returns to qualifications under different identifying assumptions.

Chapter 4 also looked at the early returns to formal education in Australia using a sample of siblings drawn from the ALS and AYS data used in Chapter 3. We began the Chapter by carrying out the same IV estimation procedure used in Chapter 3. The results we obtain for our sibling sample are broadly similar to those obtained in Chapter 3. We then compared these results with estimation procedures which assume that unobserved individual characteristics which determine wages are fixed within families. The first method involved proxying the family effect using information from both of the siblings. The second involved using a within family fixed effect estimation procedure. Both of these methods potentially allowed us to identify biases caused by the correlation of education with unobserved family attributes which determine wages. Our within family estimates of the returns to education were the same or above our OLS estimates for brothers, the same or below our OLS estimates for sisters, and always below OLS estimates for mixed sibling pairs and the sample as a whole. Both these estimation procedures assumed that family attributes (both observed and unobserved) affect both sibling's wages in an identical manner. We ended the Chapter by looking at the reasonableness of this assumption. In particular we looked at whether observed family attributes such as parent's education and occupation and the number of siblings, affected older and younger sibling's wages in different ways. We found clear evidence that they do and this finding raises doubts about the validity of the assumption on which both these estimation techniques are based. Using twin or sibling samples, may be a novel way of eliminating correlated family effects, but its validity crucially depends on assumption that unobserved family effects affect siblings in identical ways and the validity of this assumption is doubtful for our particular sample given that observed family attributes do not do this.

In Chapter 5 we looked at the returns to education for our British cohort from the National Child Development Survey, but specifically focused on the problem of omitted–ability bias and the affect this has on estimates of the returns to education. Our NCDS data has detailed information on ability tests undertaken when the individual was 7 as well as family background variables, information from the individual's teacher, formal education outcomes and labour market experience.

We began the Chapter by ignoring ability, and once again used instrumental variable techniques. Unobserved ability is only one of the possible reasons why the unobserved determinants of wages and schooling may be correlated. Therefore to control for the possibility of other correlated effects we once again relied on instrumental variable techniques. The instruments we used in this Chapter included family composition variables such as birth order and the sex composition of the individual's siblings. Birth order was not found to be important in our British sample. They also included the teacher's assessment of parental interest in the child's education when they were aged seven. We found that the children of parents who showed a lot of interest in their child's education at the age of seven had significantly better education outcomes than children whose parents showed little or no interest. We also argued that these parental interest variables, had no role in a wage equation controlling for education and could therefore be used as instruments for education. Our IV estimates of the returns to education suggested that OLS estimates which did not take into account these other correlated individual effects significantly underestimated the returns to education.

We then moved on to consider the question of omitted ability bias. We found that our proxies of ability are important determinants of both education and the level of earnings received by individuals and that conventional estimates of the returns to education which do not control for this overestimate the returns to education. However, when we took into account the effects of *both* omitted ability and other correlated individual effects, the estimated returns to education were still above OLS estimates, though (marginally) below IV estimates which did not include measures of ability.

Chapter 6 of the thesis looked at the returns to different forms of work related training in Britain. A number of issues were addressed in this Chapter. We looked at whether the estimated returns to education which were estimated in Chapter 5 were biased by not taking into account subsequent periods of work related training. We also looked at whether the returns to various types of work related training vary for individuals with different educational backgrounds. The econometric models we developed allowed us to control for the fact that training may be correlated with both transitory shocks to wages and permanent fixed effects such as ability. This involved using instrumental variable, proxy and fixed effect estimation procedures. We found that different types of training schemes have a positive and significant effect on an individual's wage outcomes. The results suggested that for men, bad productivity shocks are associated with participation in employer provided training and by not controlling for this we would underestimate the returns to such training. Participation in qualification training courses also appears to be correlated with transitory shocks and once again, estimates which do not take this into account underestimate the returns to such qualification training courses for both men and women. We also find that estimates of the returns to education which ignore work related training are biased upwards. It was also clear from the Chapter that the returns to different types of training vary across educational groups. We controlled for correlated fixed effects by using both proxy methods and fixed effect methods and both gave reasonably similar results. Controlling for correlated fixed effects did not appear to be particularly important when estimating the returns to employer provided training.

Throughout the thesis, we also focused on gender wage differentials, and specifically looked at how these vary across educational groups. Observed raw differences in the wages received by men and women generally decrease with education, though there was no significant difference for the lowest qualification group in our Australian data. If we decompose these observed differences in male and female wages for different education groups into that attributable to differences in observed characteristics, and that attributable to the observed characteristics of women being valued differently to those of men, we find that the latter effect usually dominates in Britain. The same, however, is not true for our Australian sample and the importance of the two effects varies over different education groups. We also find that part of the observed difference in the wages of men and women in our British cohort is due to the fact that men, on average, receive more work related training than women once in work.

There are a number of caveats which apply to the work which we have undertaken in this thesis. First, our estimates of the returns to education in Australia undertaken in Chapters 3 and 4, are based on a very young cohort of individuals. Our estimates do not capture average returns over the entire life cycle, but are instead estimates of the very early returns to education in Australia for a cohort of young workers. The conclusions we have drawn from these Chapters cannot be assumed to apply to the wider working population in Australia.

Secondly, we have made no attempt to deal with the problem of measurement error (or indeed other correlated individual effects) in the fixed effect within family estimation procedures used in Chapter 4. It is clear from the work of Ashenfelter and Zimmerman [12] and Ashenfelter and Krueger [11] that this can result in significant underestimation of the returns to education. The assumption that unobserved family attributes affect the wage of older and younger siblings identically (which is assumed in both models in Chapter 4) is not supported by the relationship between *observed* family characteristics and the wages of younger and older siblings. Hence the estimates from this Chapter, especially the fixed effect estimates, need to be treated with caution.

The work undertaken in Chapters 5 and 6 has also focused on one age cohort of individuals, namely those aged 33 in 1991 in Britain. Once again, it is reasonable to assume that different types of education and training are going to have varied impacts on different age cohorts and this once again needs to be borne in mind when interpreting the findings of these Chapters.

In decomposing observed gender wage differentials we have not utilised information on things like the industry and occupation of women's and men's jobs, and in our Australian sample we do not have a measure of actual labour market experience. Differences in characteristics such as these may be important in explaining these gender wage differentials and our work has not controlled for this possibility.

Finally, in this thesis we have only considered the *wage* effects of different types of education and training. Clearly, however, wages are only one aspect of a person's labour market success. Other factors such as the impact education and training has on the frequency and duration of employment and unemployment spells are also important considerations which have not been addressed in this thesis. All of these issues need to be addressed in future work.

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