

The changing distribution of male and female wages 1978-2000: can the simple skills story be rejected?

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Abstract

This paper attempts to reconcile two apparently contradictory trends in the UK labour market over the 1980s and 1990s. While wage differentials based on observed skill have risen for men, wage differentials between men and women have fallen. If women earn less than men because they are less skilled, then one would expect differences across genders to follow the same trends as differences across skills. The simplest explanation of the data is that the labour market has become more competitive, resulting in a fall in discrimination and an increase in the return to skill. As this explanation is not directly and easily testable, this paper examines its plausibility by assessing other explanations for these results.

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1 Introduction

Over the 1980s and 1990s, there have been two big changes in the structure of the labour market in the UK. First wage inequality has risen and second the relative wages of women have increased dramatically. Analyses of both trends have found a very small role for changes in the distribution of observed skill across workers. Inequality has risen because differences in wages across and within observed skill groups has risen. Relative earnings of women have increased even controlling for the increased level of education of women. These results appear to reject a view of the labour market where wage differentials are solely based on skill. To explain the increase in relative female earnings, the price of skill needs to have fallen; to explain the increase in wage inequality amongst men, the price of skill needs to have increased¹. It is the argument of this paper, therefore, that these trends can be used as evidence that the competitive framework is unable to explain the key trends observed in the labour market in the last 20 years. Labour market frictions, discrimination and institutions, must, therefore, have quantitative effects on the distribution of wages².

It is not the goal of this paper to present or test directly any particular alternative model of the labour market more consistent with the stylised facts. These trends only constitute a rejection of the law of one price under a certain set of assumptions. It is certainly possible that it is the invalidity of these assumptions (that typically have little substantive economic content) that is driving this rejection. It is this possibility that is examined in the paper. We experiment with different specifications on our main dataset, the UK Family Expenditure Surveys (FES) to see what the effect of selection and miss-specification might be. We use the British Cohort 1970 Survey and the National Child Development Survey to see whether the different allocation processes into education may be

¹Assuming no change in the distribution of unobserved skill. We discuss this issue in more detail below

²Card and DiNardo (2002) also point out the inherent contradiction in some of the patterns of changes in wage inequality with skills based explanations

driving the results. Lastly we compare data from the UK FES to Census (CPS) data from the US. We find that these trends are robust to different sorts of specifications, that the bias due to selection into education has changed in very similar ways between men and women and that the US experience is subtly but importantly different. All of this gives further weight to the interpretation placed on the data above, namely that institutions matter.

The institutional factor that is most often talked about in relationship to the increase in earnings inequality is union decline. (see Freeman and Needles 1993 for example) Union density (the proportion of workers belonging to a trade union) has fallen from a high of about 60% in 1979 to about 23% today. Men are far more likely than women to belong to a trade union or more importantly have their wages negotiated by a collective agreement (see Booth 1995). Thus, if unions increase pay, then they could increase pay differentials between men and women overall even though they might decrease pay differentials between union men and union women. Unions are associated with a more compressed distribution of pay *amongst union workers*, (see Metcalf 1982, Gosling 1998). Declines in union influence could thus very well be a cause of both the increase in male wage inequality and falls in relative female wages.

There have also been institutional changes effecting women. The key legal reforms (the equal pay act and the sex discrimination act) were been passed in the 1970s. People have argued (see Manning 1996) that these were a major cause of the increase in female relative earnings from 53% in 1970 to 66% in 1977³. There are strong reasons to suggest that this decline should have continued through to the 1980s and 1990s. First there is usually a degree of uncertainty about the precise legal implication of any substantive change to labour law until enough cases have been brought to court. For example *MaCarthy v Mrs. Smith*, which showed that it was illegal to pay women less than men who had done the same job previously was not until 1980. Second in 1984, the equal value (amendment act) was passed which brought UK equal opportunities legislations in line with the rest of Europe. This now made it illegal to pay women less than

³source FES data.

men doing the work of equal value defined by a job evaluation study, purely on the basis of gender⁴. Last if markets have become more competitive over the 1980s and 1990s then this will serve to drive discriminatory employers out of business.

There has been a plethora of papers on the increase in male wage inequality. This paper is part of the much smaller literature that tries to assess the role of labour market institutions on this increase. Like Blau and Kahn (1996), the methodology of this paper is simply to see if the predictions of the simple skills model are rejected. It differs because it exploits both variation over time and across genders rather than variation across countries⁵ The approach of this paper is distinct from the work of Bell and Pitt (1998), Dinardo, Fortin and Lemieux (1996), Gosling and Lemieux (2001) and Gosling and Machin (1995). Here decompositions analysis is used to construct counterfactual wage distributions in order to measure explicitly the role of institutions. This work has been criticised because of the assumptions needed to be made to construct the counterfactual distributions (i.e. that union status is exogenous). This paper should therefore be seen very much as a complement to this body of literature as it needs to make no such assumptions but it does not explicitly link institutional change to changes in the wage structure.

There have been quite a few papers on the declining gender wage gap in the UK and the US (see amongst others: Blau 1998, Blau and Kahn 1994, Fortin and Lemieux 1998, Harkness 1996). Some of these (Fortin and Lemieux 1998, Blau and Kahn 1994) have explicitly incorporated the changes that have been occurring to the male earnings distribution. These papers make the point that there are two factors determining the size of the gender wage gap. First is the position of women in the overall earnings distribution and second is the “penalty” for that position. The effect on female wages of women moving up

⁴Mrs. White and Others v Altons (Colchester) Ltd (1987) showed that this act had some bite. In that year Sainsbury’s, reached an out-of-court settlement with the Union of Shop Distributive and Allied Workers (USDAW) concerning pay relativities between checkout assistants and warehouse packers. (see Dickens 1993)

⁵although a comparison between the UK and the US is made

the distribution of earnings will thus be in part reversed by increases in inequality. In a world where wages were based solely on skill, one could interpret the methodologies of these paper as trying to measure the convergence of male and female skills in a world where the price of skill was rising. Instead, what we are trying to do is to see whether the convergence of male and female wages could be explained by the convergence of their skills.

The fundamental identification assumption of this paper is that apart from physical strength there are no fundamental differences between men and women. Women may be less skilled because they have less incentive to acquire human capital but, apart from strength, the skills they have are of the same type as the skill possessed by men.

The structure of this paper is as follows. The next section describes the trends highlighted above in more detail. Section 3 discusses reasons why these trends may be biased or misleading and our solutions for controlling for these biases. Section 4 presents the results and Section 5 concludes

2 Trends in relative wages from FES data

The sample we have taken from the FES is of all 23-59 year old workers in employment. Wages are constructed from data on weekly earnings divided by hours. Rather than using years of education we have constructed three education groups those leaving school at or before 16 (the majority), those leaving school at 17 or 18 (the minority) and those with some form of post school education⁶. This gives us a sample of about 130,000 workers over the 22 years.

The first panel of Figure 1 documents the growth in log male hourly wages by percentile. Here the oft-cited increase in male earnings inequality is shown clearly. The next panel shows the growth for women. Although both men and women have experienced an increase in earnings inequality there are some important differences. First the increase for women has been less marked than for men. Second wage growth has been higher for women at every percentile.

⁶see Gosling, Machin and Meghir 2000 for further discussion of this variable

Last, and most interestingly, the differences in growth rates of wages between genders appears to fall across the distribution. Thus the 10th percentile of male log hourly earnings only rose by 0.1 log points over whole period while the same percentile of female log hourly earnings rose by almost 25%. For the 90th percentile the figures are 0.5 and 0.56. This more detailed analysis suggests that it is the lowest paid (or perhaps unskilled) women who have seen their relative earnings really change. This is even harder to reconcile with the simple skill based story of events.

Likewise figure 2 documents what has happened to the difference in $\ln(\text{pay})$ across education groups, controlling for age. This is estimated from a series of OLS regressions of log hourly wages on education and a cubic function of age run separately for each year and each gender. The coefficient on a dummy variable for having some form of post 18 education compared to a base of leaving school at or before 16 is plotted. As can be seen, the “return” for men increased from 0.35 log points to 0.5 log points over the period, while it remained fairly static for women at about 0.6 log points. It appears that the education differentials amongst men are converging to the level experienced women. Figures 1 and 2 together imply that, although differences in wages between skill groups have increased for men, there have remained static for women. This, taken with the fact that female relative earnings have increased, provides further doubt on the ability of the pure skills based story to explain the data.

Figure 3 shows what has happened to differences in pay between men and women, controlling for age for each education group. The first thing to note is that differences between men and women are more marked at lower levels of education. Thus one interpretation of the higher return to education amongst women is that discrimination falls as education rises⁷. The second thing to note is that while differentials amongst the highest education group have remained fairly static, they have fallen quite significantly amongst the lowest group. If it is increases in demand for skill that is driving the slow growth in wages amongst

⁷Later on we show that the same pattern is found when we look across the wage distribution, the gap between the male and female wages at the 10th percentile is higher than at the 50th. At the 90th percentile there is a very small gap indeed

unskilled men, why are unskilled women doing so well? On the other hand, increases in the return to skill, coupled with a fall in discrimination affecting unskilled women would easily predict the patterns we observe in the data.

We might explain the increase in female relative wages by the fact that successive generations of schools, expecting to be more attached to the labour market, are working harder at school. What is less clear is that why this increase in effort should be most dramatic amongst those girls leaving school at the minimum school leaving age amongst whom there is no upward trend in participation over time. It is the different experiences across education groups that is the strongest indication, therefore, that discrimination and/or institutions may have played a role. There are, however, two ways in which the skills based story could be rescued. The first is that the trends we observe are simply an artefact of selection effects and miss-specification. The second is that the uni-dimensional skills based story is too simplistic and that the shifts we see in relative wages have been driven by more complicated changes in the structure of demand. The following section examines these points in more detail

3 Rescuing the Skills based Interpretation

3.1 Endogeneity and misspecification

The results presented above were obtained from regressions of the following form

$$w_{it} = \alpha_{t,g} + \beta_{t,g}^1 age + \beta_{t,g}^2 age^2 + \beta_{t,g}^3 age^3 + \delta_{t,g}(S = 2) + \delta_{t,g}(S = 3) + \varepsilon_{it}$$

where age , S is discrete variable taking the value 1 if the worker left school at or before 16, 2 if the worker left school at 17 or 18 and 3 otherwise, t and g are subscripts for time and gender and ε is an error term. This is probably the most common wage equation estimated. Assuming that ε is uncorrelated with all the regressors in each time period, we will obtain consistent estimates of the β s and the δ s. There are however strong reasons to suggest not only that ε is correlated with age and S so that the level of the estimated parameters

is wrong but also and more importantly that this bias differs across genders and will change over time. This we can say nothing about how the return to education has changed over time and how it differs across men and women. We now discuss what are the likely sources of bias and show how we can attempt to measure and/or control for it.

3.1.1 Selection effects

It is well known that estimates of the distribution of wages that do not control for the possibility that workers are not randomly drawn from the population as a whole are likely to be inconsistent. In addition the bias will increase with the extent of selection⁸. Thus it is certainly possible that the raw results presented could simply be an artefact of the changing composition of the workforce vis a vis the population as a whole⁹. For example, the increase in female labour force participation has been driven in part by the changes amongst married educated women with children. If this group of women have lower productivity then this will serve to bias downwards the measured trend in the difference in female wages across education groups as the higher educated group because more dominated by women with less labour market experience. The most natural way to proceed, and the one we follow, is to obtain selectivity corrected estimates of the gender wage differential and the return to education using the methodology and framework of Heckman (1974,1976).

Although identification is possible through functional form, in practice results obtained without an exclusion restriction are typically not robust. We exploit the variable used by Blundell et al. (1999) to identify separately the probability of work from the determination of wages. This variable is the level of entitlement to state benefits that the individual would receive if she (and her partner) were both out of work. This is calculated from the Institute for Fiscal Studies' (IFS) tax-benefit model¹⁰. In the UK benefits are means tested so the

⁸see Heckman (1974, 1976)

⁹Blundell Reed and Stoker (2002) examine this issue in detail for men. Blundell, Gosling Ichimura and Meghir examine this whole issue of selection into work in more detail

¹⁰see Blundell et al (1999) for more details

variation in entitlement across individuals is driven in part by differences in perceived needs, those with children get higher levels of benefits and so on. At any point in time, therefore it will be impossible to separate out the effects of the policy variable from the effects of factors determining benefit entitlement. This will be a problem if it is believed such factors are correlated with unobserved skill in some way. (Low waged women may be more likely to have children for example). As we are modelling participation throughout the 80s and 90s we can exploit variation over time in entitlement driven by policy changes and so control for differences in the cross section. This is consistent so long as it is assumed that correlation of things like number of children with the unobservables in the wage equation is constant over time.

3.1.2 Experience effects

In common with many other studies *age* is used essentially to proxy labour market experience. If adult employment rates are 100%, then age minus years of schooling will equal experience. Employment rates are not 100%, however, many women spend time out of the labour market and work in the home instead, men and women spend time searching for work or simply being unemployed. The first bias this introduces is measurement error¹¹. In addition as the variance of experience given age has to increase in age, there will be heteroscedasticity. Most importantly the expected level of experience given age will vary across groups. Thus the δ s will be biased upwards insofar as those with more education are likely to have more experience at each age.

Female labour market participation has been changing over time and thus we might expect that the average amount of experience at each level of age should also rise¹². This means that our estimates of α and the β s for women will increase as the downward bias falls. If the covariance between experience and education falls our estimates of the δ s will also decrease. It is thus certainly

¹¹see Bollinger 2002 for a discussion of the relationship between proxy variables and measurement error

¹²this is not necessarily so if the increase in participation has come from women with low levels of experience who previously could expect never to be in the labour market again (see above)

possible that the results we presented above could be spurious. It might be thought that the obvious thing to do here would be to use experience instead of age. This is not so. First experience is not observed in any data which includes information of wages over the 80s and 90s. Second there is a problem of causality, if people chose to work dependent on the wages that they are offered it will be those who receive lower wage offers who have lower levels of experience. Thus including experience as a regressor will introduce another source of bias. Instead we simply focus our analysis on younger workers (25 year olds).

Of course there will be differences in experience amongst 25 year olds. For the lowest education group some will have the full amount (9 years) and some may only have 1 or 2 years. Thus, this approach does not make the problem go away but it should seriously reduce the potential for bias. By focusing on this group we hope to abstract from the systematic difference in male and female experience rates found across older workers. The mid 20s is an age when unskilled women typically leave the labour market to have children and those who will be out for some time are unlikely to be in our sample.

3.1.3 Education

Education, as a choice variable, is very likely to be related to unobserved ability. Thus when we compare wages across education groups we do not know how much of the difference is due to the effect of education and how much is due to the effect of unobserved ability. This is, however, the least of our problems when trying to isolate how much influences changes in prices of skills have had on the wage structure. The fact that education is potentially endogenous biases not only estimates of the return to education, but how it differs across groups and changes over time. It also biases estimates of the gender wage differential. To see this note that

$$E(w|S, g, t, age = 25) = \alpha_{g,t} + \delta_{t,g}(S = 2|age = 25) + \delta_{t,g}(S = 3|age = 25) + E(\varepsilon|S, g, t|age = 25)$$

where the α and δ s are defined as above. As education is potentially endogenous we cannot make the assumption that $E(\varepsilon|S, g, t)$ is zero.

Then the estimated conditional gender wage differential for the lowest education group will be

$$\alpha_{m,t} - \alpha_{f,t} + E(\varepsilon|S, m, t) - E(\varepsilon|S, f, t)$$

Any change in the gender wage differential could thus be driven by changes in $E(\varepsilon|S, m, t) - E(\varepsilon|S, f, t)$ (unobserved skill) as well as changes in the α s (underlying prices) even if there has been no change in the distribution of ε in the population. It is easy to see that the same problem will occur when looking at difference across education groups.

Participation in education has changed significantly over time. In 1979 16% of male and 15% of female 23-28 year olds had some form of post 18 education¹³. In 1999, the proportions had risen to 29% for men and 27% for women. It is thus highly unlikely that the distribution of unobserved ability has remained constant while the proportion in higher education has almost doubled. These trends further underline the need to address the problem of the endogeneity of education before making any conclusions about changes in the return to skill or gender wage differentials.

The problem here is slightly different from the problem of estimating the causal effect of education and earnings. We are concerned with changes in the price of human capital overall, rather than any particular component of it. Thus instrumental variable (IV) procedures would be inappropriate as the parameter they would estimate would be the effect of education on earnings, conditional on unobserved ability. A more natural strategy would be, if possible, to include measures of ability directly into the earnings regressions and then see what happened to prices of skill overall.

As many components of ability (such as drive or motivation) are likely to be unobservable as well as unobserved, this last procedure will be quite difficult.

¹³source FES

In addition the data we have on ability in the UK does not include data on wages over the 1980s and 1990s. Our strategy instead is to establish how much the correlation between education and ability may have changed over time and whether these changes could have been driving the results. We do this in two ways. First we present a simple model of allocation into education that can allow estimation of the correlation between education and ability from observed changes in the distribution of education. Second, and most convincingly we use data from the National Child Development Survey (NCDS) and the 1970 British Cohort Study (BCs70). Each of these datasets follow a cohort of individuals born in a certain week. The NCDS covers those born in 1958 and the BCs70 those born in 1970. Both these datasets contain results of aptitude tests taken at 10/11 and information on educational attainment. Thus it will be possible to see directly how the relationship between these two skill measures changes across cohorts.

3.2 Decline in demand for muscle versus increases in demand for skill

Behind the simple skills story lies a model of wage and productivity determination with one dimension of skill. Women earn less than men simply because discrimination elsewhere in society and career breaks due to child birth mean they invest less in human capital and so have lower amounts of this skill. This model does not, however, reflect the relevant key physical difference between men and women. Men are stronger. Historically many jobs required (and some still do require) strength. A better interpretation of the changes over the 1980s and 1990s might be that the demand for “muscle” has shifted downwards. So long as muscle is not perfectly correlated with and substitutable for other dimensions of skill, this will result in an increase in the measured return to education for men, and no real change for women (i.e. what we have observed). This is similar to the model examined by Welch (2000).

To see this, consider the following simple model. Let output in each firm be some function of inputs of human capital (H), physical strength (M) and other

inputs:

$$Q_j = F_j(H, M, A)$$

competition between firms and workers ensures that marginal products of each input are equated across firms. Let α equal the marginal product of H and δ the marginal product of M . Workers are endowed with and invest in different amounts of H and M and the wage they receive will simply be

$$w_i = \alpha H_i + \delta M_i$$

Now assume for simplicity (without loss of generality) that women have no M and that amongst men M is uncorrelated with H ¹⁴. Then the proportional return to skill for women will be

$$\frac{1}{H_i}$$

and for men it will be

$$\frac{1}{H_i + \frac{\delta}{\alpha} \bar{M}}$$

where \bar{M} is the mean endowment of muscle across men. As δ, α and M are all positive, it is easy to see that this simple model predicts the return to education should be much higher for women than for men as indeed is the case (see figure 2 above). In addition as δ falls the return to education for men rises. The data appear to be more consistent with a fall in δ than a rise in α .

Similarly the ratio between male and female wages, conditional on H will be

$$\frac{H}{H + \frac{\delta}{\alpha} \bar{M}}$$

¹⁴as the opportunity cost of education is falling in M in practice we should see a negative relationship between M and H . This will exaggerate the results described below

i.e. decreasing in H and increasing in δ , just as the gender wage differential falls across education groups and has decreased over the 1980s and 1990s. Thus it appears that this simple model is better able to explain the trends and patterns in the data described in section 2 than a simple uni-dimensional skills story. The change in the structure of demand is better described by a decline in the demand for muscle, rather than an increase in the demand for human capital or cognitive skills (H).

Rather than testing this model directly on the data, we attempt to establish whether it is as good a fit for US data as well as the UK. Under the assumption that any technical change or change in the structure of demand should effect both countries in the same way, then we should see the same trends in both countries. If, on the other hand, institutions have a significant effect on the wage structure, then we could see different trends in both countries reflecting differences in their institutional framework.

4 Results

4.1 Selection effects: FES data

The first set of results we present come from the FES data. This dataset is used to find estimates of wage differentials across education groups and gender that are robust to non-random selection into work and experience effects. To avoid small sample problems we estimate the wages and employment probabilities of 25 year olds by taking 23-28 year olds and using weights so that the youngest and the oldest in the sample have less influence on the resulting parameters¹⁵. The total number of observation we have in our data is just over 27,000 which includes just over 22,400 workers.

4.1.1 The probability of work

The procedure we use to obtain the selectivity corrected estimates of the parameters in the wage equations is, following Heckman (1976) first to estimate

¹⁵the weights we use are “triangular” and constructed in the following way: $wt = (x - 1)^2(x + 1)^2$ where $x = (age - 25)/3$.

the probability of observing each individual in work, given their characteristics.

$$P_i^* = z_i\gamma + \eta_i$$

In the equation above P^* denotes the net utility difference between work and leisure, z is a set of observed covariates reflecting wages and reservation wages and η includes everything that effects P that is not in z . P^* is not observed but we assume that if we see someone in work P^* must be positive. If in addition we assume that η is distributed normally with mean zero and variance 1, then we can estimate the γ s and hence $\Pr(P_i > 0|z_i)$ using a probit. This is what we do

The next problem we face is how to treat the self-employed. We chose to treat the self-employed as workers for whom we have missing data on their wages¹⁶. Thus we include them as workers when we estimate the probability of work.

We separated our sample into four, two education groups (those leaving school at or before 16 and those leaving after 16) and the two genders. We also control for family status and regional effects that might influence benefit entitlement but may also be correlated with unobserved factors in the wage equation. For the highest education group we include a dummy variable for those leaving education before 19.

The results from the probits can be seen in table 1 below. The first row shows the coefficient on benefit income to be negative (as expected) in all cases. The marginal effect is relatively small however, implying that an increase in benefit entitlement of £100 per week in 2001 prices would only reduce probability of work by less than 6 percentage points. It is however strongly statistically significant for all groups apart from higher educated men. The imprecise estimates of the benefit effect for higher educated men are probably due to their higher

¹⁶This is not usual practice, typically the self-employed are simply excluded from the whole analysis. Only under the assumption that the self-employed are randomly drawn from the population as a whole is this common practice legitimate, however. (see Gosling and Reed 2002 for a full discussion of this problem) We believe our assumption is more plausible

participation rates, the benefit variable has less to explain. In addition the fact that we have controlled for both family status and regional variable means that we have taken away many of the sources of variation in this variable.

Table 1: Probit estimates of the probability of work

	Men		Women	
left school:	at or before 16	after 16	at or before 16	after 16
Benefit Income				
β	-0.144	-0.007	-0.143	-0.155
	<i>0.040</i>	<i>0.040</i>	<i>0.036</i>	<i>0.034</i>
$dF/dx \times 100$	-0.033	-0.001	-0.057	-0.041
	<i>0.009</i>	<i>0.007</i>	<i>0.014</i>	<i>0.009</i>
Part of Couple (β)	0.805	0.518	0.023	-0.053
	<i>0.065</i>	<i>0.087</i>	<i>0.060</i>	<i>0.065</i>
Number of Kids (β)	-0.187	-0.200	-0.713	-0.713
	<i>0.039</i>	<i>0.062</i>	<i>0.034</i>	<i>0.049</i>
Couple x NKids (β)	-0.130	-0.133	0.161	-0.064
	<i>0.047</i>	<i>0.086</i>	<i>0.039</i>	<i>0.060</i>
Left School at 17 or 18 (β)		0.025		-0.160
		<i>0.058</i>		<i>0.049</i>
Constant (β)	0.486	1.194	0.931	1.754
	<i>0.137</i>	<i>0.231</i>	<i>0.134</i>	<i>0.176</i>
Regional Dummies	✓	✓	✓	✓
Year Dummies	✓	✓	✓	✓
Log Likelihood	-2637.93	-1214.80	-3696.41	-1972.03
Number of Obs	6288	3726	6509	4798
$\Pr(W = 1 G)$	0.828	0.891	0.542	0.782

Notes:

weighted probit estimates given

standard errors in italics

sample: all 23-28 year olds

β denotes coefficient estimate

dF/dx denotes marginal effect at the mean of the dependent variable G refers to a particular gender and education group

4.1.2 Wages

The next stage of the procedure is to use the coefficients from the probit equations to find an estimate of η for those observed in work. This will be non zero

conditional on z as it is likely that those observed in work with higher levels of benefit entitlement have higher wage offers, lower fixed costs of work and/or like leisure less, conditional on other covariates. This is the source of selection bias.

$$P = 1 \text{ implies } z_i\gamma + \eta_i > 0 \text{ or } \eta_i > z_i\gamma + \eta_i > 0$$

As $\eta \sim N(0, 1)$ then we can say that

$$E(\eta | > -z_i\gamma) = \frac{\phi(-z_i\gamma)}{1 - \Phi(-z_i\gamma)} = \frac{\phi(z_i\gamma)}{\Phi(z_i\gamma)}$$

where $\phi(\Phi)$ is the standard normal density (cumulative) probability function¹⁷. The Heckman “trick” is to include this expectation or “mill’s ratio” in the wage equation. Assuming that ε (the error term in the wage equation) and η are jointly normally distributed, the expected value of the coefficient on this mills ratio will be ρ (the correlation between η and ε) \times σ (the standard deviation of ε). Inclusion of this variable will remove all systematic correlation between the regressors and ε induced by selection.

Table 2 shows the selection effects on wages. If we ignore the results for higher educated men, we see that our estimates of ρ are large, positive and significant. This suggest that selection bias is important and that those who are working have higher wages than those observed out of work. For higher educated men, the estimate of ρ is negative (although not significant). This could be a weak instruments problem (see Bound et al 1995) as the coefficient on the benefit variable is not significant in the first stage probit, but it also reflects that this group is perhaps not particularly selected as almost 1 in 10 people work. When we obtain wages adjusted for selectivity we therefore use the simple OLS results for this group.

The coefficients from these regressions were then taken to obtain predicted wages for each individual (including those not observed in work). For each

¹⁷this uses the well known results on the moments of the truncated normal distribution (see for example Maddala 1983 pp 365 to 371)

Table 2: Estimates of selection effects on wages

	Men		Women	
	at or before 16	After 16	at or before 16	After 16
$\sqrt{\sigma^2(1 - \rho^2)}$	0.329	0.369	0.342	0.356
$\sigma\rho$ (se)	0.860 (0.114)	-0.497 (0.344)	0.535 (0.113)	0.489 (0.115)
ρ	0.934	-0.806	0.843	0.808
σ	0.848	0.384	0.404	0.365

Notes:

These results were obtained from weighted regressions of wages on a set of year dummy variables plus the control variables as in the probit estimates above. Estimates were obtained for each group separately

The root mean squared error of the regression gives $\sqrt{\sigma^2(1 - \rho^2)}$ the coefficient on the 'mills ratio' gives $\sigma\rho$, σ and ρ can then be obtained by simple algebraic manipulation.

Standard errors adjusted for the inclusion of a generated regressor.

individual we obtained two predictions, first one from a simple OLS regression, not including the mills ratio, second one using the selectivity adjusted regression coefficients. The data were then aggregated into cells defined by time, education group and gender. For each cell, we defined two values of the mean wage. The uncorrected one was simply the mean of the simple OLS prediction for each cell, the corrected one was the mean of the selectivity adjusted prediction. This data was used to draw the graphs below.

Figure 4 shows what has happened to wage differentials across education groups for men and women. Looking at the first panel, the one that shows the results uncorrected for selection, it appears that much the same trends exist amongst younger workers as in the population as a whole. Differences across education group have been rising for men but have remained fairly static for women. The second panel shows that once we control for selection, the differences between men and women become more marked. For men differences between education groups grow faster over the 1980s and do not fall as much over the mid 1990s. For women, they rise slightly over the 1980s and fall slightly over the 1990s. Differences in the trend in the return to education across men

and women thus appear to be neither a result of selection or of changes in the distribution of experiences. These graphs also show that the differences across education groups are biased downwards when we do not control for selection¹⁸.

Figure 5 shows what has happened to the gender wage differential across education groups. Some important differences emerge. First in the population as a whole the gender wage differential was rising for educated workers until 1990 and then falling slightly after that, amongst younger workers the rise over the 1980s is less marked and the fall over the 1990s is more dramatic. Thus we can probably attribute some of the rise in the gender wage differential amongst educated workers to the fact that there are more educated women working now with lower levels of labour market experience. Similarly when we control for selection, there is no increase in gender-wage differentials amongst this group. This further underlines that experience and composition effects matter. They are unlikely to be able to explain everything though. The decline in gender wage differentials is much more dramatic amongst the low educated group, especially when we control for selection. The *differences* in the trend across groups is in fact more marked when we control for selection and we concentrate just on younger workers than when we look at the trends described in section 2.

To sum up this section, the measured return to skill has appeared to rise for men and remained static for women. Gender wage differentials have fallen, especially amongst the low skilled. These findings are robust to the problem of miss measuring experience and selection into work. Thus the conclusion of this section is that we are still left with the apparent contradiction of why gender wage differentials (especially those of the low skilled) should have fallen in a time when the price of skill is rising. The next section looks at whether this could be due to biases caused by the non random allocation of people into education.

4.2 Endogeneity of education

In this section we do two things, first we present a simple model of allocation into education that allows us to estimate the bias in the return to education

¹⁸see Blundell, Reed and Stoker 1999 for a similar finding

from data on the proportion of people in each education group. Second we use cohort data to measure how the correlation between observed ability measures and education has changed over time. The conclusions of both are similar, namely that it is unlikely that it could be biases in the return to education that could be driving the results

4.2.1 A simple model of education

Consider a world where selection into education was based solely on ability and where education takes two values, 0 or 1. Both the returns to education R and the costs C increase in ability A . R is increasing faster in A than C , however so that there exists a threshold of A , below which nobody is educated and above which everybody is educated. Assume in addition that A is continuous and distributed log normally. Now let $a = \ln(A)$. For illustration, in the first panel of figure 6, the vertical line denotes the threshold values of a , \bar{a} , superimposed on the distribution function. By definition therefore

$$\Pr(E = 0) = \Pr(a < \bar{a})$$

and as a is distributed normally:

$$\bar{a}\sigma + m = \Phi^{-1}(\Pr(E = 0))$$

where $\Phi^{-1}(\cdot)$ is the inverse of the standard normal cdf, σ is the standard deviation of a and m is its mean. For simplicity assume that $\sigma = 1$ and $m = 0$. By using the results on the truncated normal distribution, we then can compute

$$E(a|E = 0) = \frac{-\phi(\bar{a})}{\Pr(E = 0)}$$

and

$$E(a|E = 1) = \frac{\phi(\bar{a})}{\Pr(E = 1)}$$

If we know $\Pr(E = 1)$ and assume a is distributed normally with mean zero and variance 1 therefore, we can easily compute the mean of a in each education group. This is illustrated in the second panel of figure 6. Likewise the last panel plots the difference. This can be interpreted as what the mean difference in log wages across the two education groups would be if education effects were zero. They are always positive and they reach a minimum at 0.5. If $\Pr(E = 1)$ increases from 0.5 to 0.6, therefore than the measured difference in wages would rise even if there had been no change in the return to education.

We can use this simple model, extended to three groups, to identify $E(a|E = 0, 1, 2)$ for each year and for men and women, assuming a is normally distributed with mean zero and variance 1. The key economic assumption here is that the distribution of a does not shift over time or vary across genders. Figure 7 plots the difference between these expectations across education groups. The implied bias is higher for women than for men. This might explain why the measured return to education is also much higher for women. There is however, little evidence that the bias is falling faster for women than for men, however. In fact, the right hand panel shows the bias in the estimate of the difference between the highest and the lowest education group to be increasing for women over the 1980s. Figure 8 indicates why this is the case, although participation in education is slightly different between men and women, they have changed in very similar ways over the 1980s and 1990s.

These results are based round the assumptions that a) ability is the only factor determining allocation into education at any point in time, b) it is normally distributed. These assumptions are not testable or particularly plausible so we now use data from the BSc70 and the NCDS to examine the changing correlation between education and ability over time.

4.2.2 Evidence from the BCs70 and NCDS datasets

Both the BCs70 and the NCDS sample were tested at 10/11 on their verbal and mathematical ability. These were not IQ tests and so reflect ability acquired through schooling up to 11 and parental inputs as well as “innate ability”. We

have aggregated the scores on both these tests to find an aggregate measure of the respondent's ability. The scale of this aggregated measure has no real economic meaning and so it can only be used to rank individuals by their ability. We now see how participation in education varies across this ranking.

For each cohort (those born in 1958 from the NCDS and those born in 1970 from the BCs70), we defined deciles of the test score separately for men and for women. We then found the proportion in each decile/group cell who were in full time education after the age of 16. These are plotted in figure 9. As expected there is a strong positive relationship between ability at 11 and the probability of staying on at school past the age of 16. This is clear for both men and women, in addition, the increase in participation in education has come mostly from those of lower ability so that the correlation between ability and education should become slightly less marked over time. Note however, that it is men from the bottom three deciles who have increased their participation the fastest, while it is women from below the 60th percentile. This suggests that educated men are becoming less positively selected at a faster rate than educated women. Women also appear to be less selected than men to start with¹⁹.

It is possible to use these figures to predict the conditional distribution of ability for those in the higher educated group. Note that

$$\Pr(A < A^q | E = 1) = q \frac{\Pr(E = 1 | A < A^q)}{\Pr(E = 1)}$$

where A^q is the q^{th} quantile of the ability distribution, A is ability, $E = 1$ denotes membership of the higher educated group. As we cannot measure A^q , we just plot the right hand side of the equation above against q . This will give another indication of how the degree of selection may be changing over time. This is shown in figure 10 In each panel the straight line denotes the counterfactual distribution if $\frac{\Pr(E=1|A < A^q)}{\Pr(E=1)} = 1$ for all A^q . The extent of selection can be

¹⁹this contrasts with the finding of the previous subsection. This suggests that the assumption that ability is the only determinant of education is perhaps invalid

assessed by looking at the gap between the conditional distribution functions and this line. Once again, it appears that women are less selected than men but this gap is narrowing over time

Table 3 underlines the results from this analysis. The left hand side of the table shows what has happened to selection into education by ability. The probability of having a test score less than the median is used. This picks up the probability of observing an educated worker who is from the bottom half of the ability distribution. Men are less selected over time but this gap has become less marked. The right hand side of the table shows what has happened to wage differentials. These are shown for when the cohorts were 25 and the education group is at or before 16 versus past 16. The measured return to education has gone up faster for men than for women. This is despite the fact that ability has fallen faster for men than for women. Thus endogeneity of education is unlikely to be able to explain the differences in the changes in the return to education between men and women.

Table 3: Changes in selection into education and educational wage differentials

	$\Pr(A < A^{q=50} Ed = 1)$			$E(w Ed = 1) - E(w Ed = 0)$		
	1958	1970	$\Delta 58-70$	1958	1970	$\Delta 58-70$
<i>Men</i>	0.237	0.343	0.106	0.390	0.494	0.104
<i>Women</i>	0.292	0.391	0.099	0.508	0.541	0.033
<i>Difference</i>	0.056	0.048	-0.007	0.119	0.047	-0.071
Sources	NCDS & BCs70 data			FES data		

Notes

$A^{q=50}$ is the median level of ability

wage differentials are computed from the FES results described in the earlier section. They are based on wage differentials at the age of 25 and are corrected for selection

It appears, therefore that experience effects, selection into work or into ed-

ucation are unlikely to be able to explain why the return to skill rose faster for men than for women. We compare the UK and the US to assess whether the data fit a decline in demand for “muscle” better than an increase in demand for education

4.3 CPS data

This next section compares what has happened to the gender wage differential across the wage distribution in the UK and the US. The remaining skills based explanation we have left for our data is that the changes in the structure of demand have been slightly more complicated than an increase in the price of an uni-dimensional “skill”, the other more ‘statistical’ explanations do not appear to have much power. A model was presented where both “muscle” and human capital are inputs into production. The key here is that as they are neither perfectly correlated or substitutable with each other then an decrease in demand for muscle will have very different effects on the wage structure from an increase in demand for human capital. If this “muscle” story is correct then, under the assumption any technical change or change in the structure of demand should effect both countries in the same way, then we should see similar trends in both countries. This is what we examine.

As it is hard to obtain education measures in the CPS and the FES that are directly comparable for the entire period²⁰, we use rank in the earnings distribution to proxy endowment of H (human capital). Earlier it was assumed that H and M were uncorrelated. While this assumption of uncorrelation between cognitive skills and muscle is plausible ex ante, we are likely to see a negative correlation ex post. as those with high M face higher opportunity costs of acquiring new skills. To conclude that those at the top of the earnings distribution have higher H than those at the bottom, therefore, we just need to assume additionally that productivity of H is higher than the productivity of M . Then workers higher up the earnings distribution of a particular gender must have

²⁰this is due mainly to the different education systems in the two countries. UK children can leave at 16 with some form of qualification, US children have to wait until 18.

higher endowments of H , *on average*.

The US data we use is from the March outgoing rotations sample from the CPS. From this we took all workers between 23 and 28 who had non missing values on both the wage and the hours questions. Although the structure of the earnings questions have changed over time in the CPS, we feel that we have managed to get a fairly consistent series. We took a similar sample from the FES. Both datasets were then simply aggregated by year and gender to find the 10th, 50th and 90th percentiles and the mean. We then found the gender wage differential for each of these moments of the distribution for each country at each point in time.

The results are plotted in figure 11 below. At both the mean and the median, the US and the UK pictures are quite similar, both in terms of levels and in terms of changes. Gender wage differentials on average have fallen from about 30% to about 10% over the last 20 years for younger workers. Looking at the 10th and the 90th percentile, however, some important differences emerge. First wage differentials associated with gender are much higher at the top of the distribution in the US and higher at the bottom of the distribution in the UK. Second wage differentials have fallen faster amongst low paid women in the UK and amongst high paid women in the US. This goes clearly against the “muscle” story. The muscle story predicts that wage differentials between men and women should fall across the distribution and fall fastest amongst the low paid. Although this is clearly the case in the UK, it is not in the US.

This comparison suggests that the technological model that fits the data for the UK provides a poor fit for US. If wage differentials solely reflect skills, then the US and the UK must have different underlying technologies. We believe this is unlikely to be the case which leads to the conclusion that institutions and labour market frictions must have quantitative effects on the distribution of wages. In the UK, institutional changes were likely mostly to affect unskilled women. The decline in union power allowed them to catch up with their unskilled counterparts. Equal Value legislation affected directly relative wages between unskilled manual men and unskilled manual women as the case of

Sainsburys v. USDAW showed. Here Sainsburys settled out of court and agreed to pay those working the tills (mostly women) the same as those loading the lorries in the warehouse (mostly men). In the US, in contrast, changes were likely at best to miss women at the bottom of the wage distribution and at worst effect them adversely. There was a much smaller decline in unionisation (see Gosling and Lemieux 2001). The decline in the real value of the minimum wage hit unskilled women the most. In addition the increase in affirmative action policies are likely mostly to benefit women heading for managerial or professional positions.

5 Conclusions

It is the argument of this paper that the increase in female relative earnings over a period in which differentials based on skill were rising for men is puzzling. If women are paid less than men because they are less skilled, then we should expect to see differentials rising as the price of skill rises. The stylised facts appear to suggest, therefore, that wage differentials are based on other factors apart from skills. The paper offers some alternative explanations for the data, by which the skills based model can be “rescued”. First it is argued that the trends we observe are simply an artefact of selection and misspecification. It is shown, however, that biases caused by the selection process into work, the selection processes into education and by the changing distribution of experience across age groups cannot explain the different labour market experiences of men and women. Second it is argued that the data might fit better a decline in the demand for “muscle” rather than an increase in demand for education. This would suggest that we should see the same pattern in US as we see in UK data, namely that the increase in female relative wages should be faster at the bottom of the distribution. In the US we see the opposite, it is the well paid women who have done the best. Thus both the explanations offered are rejected. This paper thus offers support for the view that institutions matter in the determination of wages by showing that skills explanations, by themselves, provide a poor fit for

the data.

Women investing more in their human capital is likely to be an important of the reason why their relative wages rose. Increases in the price of skills are likely to have been an important reason why wage inequality amongst men has risen. These changes do not explain the difference in experiences across the distribution of female wages and that the return to education has remained static for women, however. This is the puzzle and the reason why we argue that institutional changes must have accompanied changes in the structure of demand and increase in female skills.

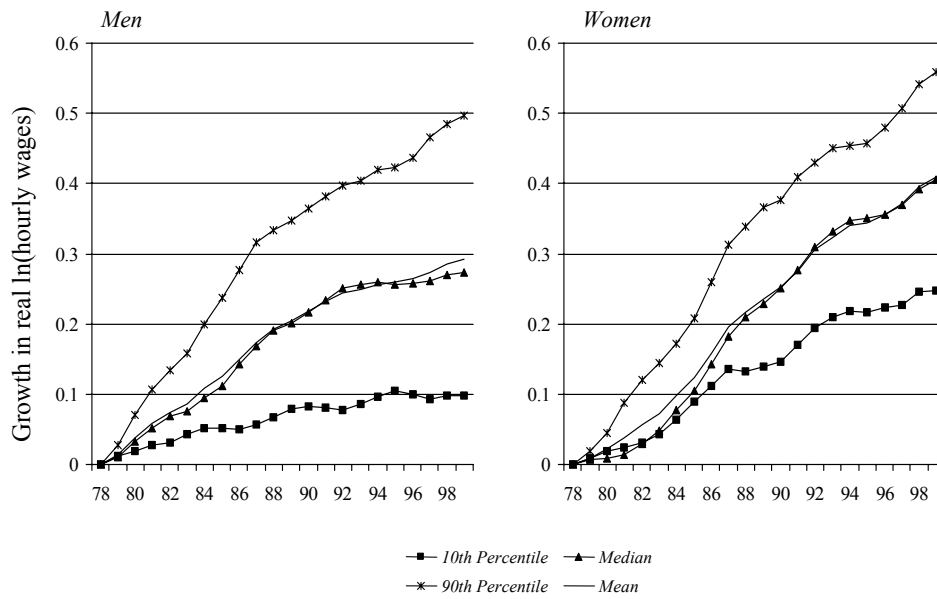
References

- [1] Bell B and M Pitt (1998) 'Trade union decline and the distribution of wages in the UK: evidence from kernel density estimation' *Oxford bulletin of economics and statistics*, November, Vol.60, No.4, pp.509-528
- [2] Blau F and L Kahn (1994) 'Rising wage inequality and the U.S. gender gap' *American economic review*, May Vol.84, No.2, pp.23-28
- [3] Blau F and L Kahn (1992) 'The gender earnings gap - learning from international comparisons' *American economic review*, May, Vol.82, No.2, p.533
- [4] Blau F and L Kahn (1996) 'International differences in male wage inequality: institutions versus market forces' *Journal of political economy*, August, Vol.104, No.4, pp.791- 837
- [5] Blau F (1998) 'Trends in the well-being of American women, 1970-1995' *Journal of economic literature*, March Vol.XXXVI, No.1, pp.112-165
- [6] Blundell R, A Gosling, H Ichimura and C Meghir (2002) 'Changes In The Distribution Of Male And Female Wages Accounting For Employment Composition' IFS mimeo

- [7] Blundell R, H Reed and T Stoker (1999) 'Interpreting movements in aggregate wages: the role of labour market participation' IFS working paper 99/13 London
- [8] Bollinger C (2002) 'Measurement Error in Human Capital and the Black-White Wage Differential', *Review of Economics and Statistics*, forthcoming
- [9] Card D and R Freeman (1993) *Small Differences that Matter; Labour markets and IN come maintenance in Canada and the United States*
- [10] Card D and J DiNardo (2002) 'Skill-biased technological change and rising wage inequality: some problems and puzzles' *Journal of labor economics*, Oct Vol.20, No.4, pp.733-783
- [11] Bound J, D.A Jaeger, R.M. Baker, (1995) Problems with instrumental variables estimation when the correlation between the instruments and the endogenous explanatory variable is weak, *Journal of the American Statistical Association* 90, 443-450
- [12] Dinardo, Fortin and Lemieux (1996) 'Labor market institutions and the distribution of wages, 1973- 1992: a semiparametric approach' *Econometrica*, September, Vol.64, No.5, pp.1001-1044
- [13] Dickens, Linda (1993), *Collective Bargaining and the Promotion of Equality: The Case of the United Kingdom. Equality for Women in Employment: An interdepartmental project.* ILO, Geneva
- [14] Fortin and Lemieux (1998) 'Rank regressions, wage distributions, and the gender gap' *Journal of human resources*, Summer, Vol.XXXIII, No.3, pp.610-643
- [15] Freeman and Needles (1993) 'Skill differences in Canada in an era on rising wage inequality' in Card and Freeman (1993)
- [16] Gosling A (1998) *The Determination of Union Status and Wages in British Establishments'* Department of Economics University of Essex working paper # 491

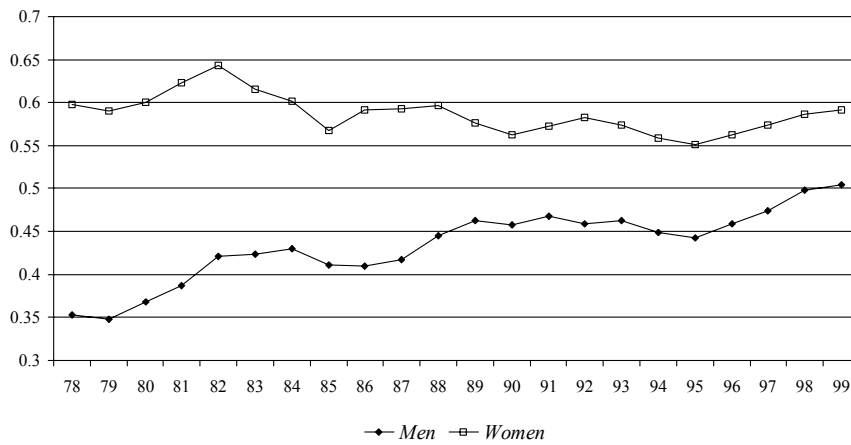
- [17] Gosling A and T Lemiux (2001) 'Labour market reforms and changes in wage inequality in the United Kingdom and United states' NBER working paper # 8413
- [18] Gosling A and S Machin (1995) 'Trade unions and the dispersion of earnings in British establishments, 1980-90' *Oxford bulletin of economics and statistics*, May, Vol.57, No.2, pp.167-184
- [19] Gosling A, S Machin and C Meghir (2000) 'The Changing Distribution of Male Wages in the U.K.' *Review of Economic Studies* October, 67,4
- [20] Gosling A and H Reed (2002) 'self-employment selection and the wage structure' IFS mimeo
- [21] Harkness S (1996) 'The gender earnings gap: evidence from the UK' *Fiscal studies*, May, Vol.17, No.2, pp.1-36
- [22] Heckman J (1974) 'Shadow Prices, Market Wages and Labor Supply' *Econometrica* 42:679-94
- [23] Heckman J (1976) 'The common structure of statistical models of truncation, sample selection and limited dependent variables and a simple estimator for such models' *Annals of Economic and Social Measurements* 5: 475-92
- [24] Kahn (1998) 'Against the wind: bargaining recentralisation and wage inequality in Norway 1987-91' *Economic journal*, May Vol.108, No.448, pp.603-645
- [25] Maddala G S (1983) *Limited Dependent and Qualitative Variables in Econometrics* Cambridge University Press
- [26] Manning A (1996) 'The equal pay act as an experiment to test theories of the labour market' *Economica*, May Vol.63, No.250, pp.191-212
- [27] Metcalf D (1982) 'Unions and the distribution of earnings' *British Journal of Industrial Relations* 20(2) 170185

Figure 1: Real Hourly Earnings by Percentile 1978-1999



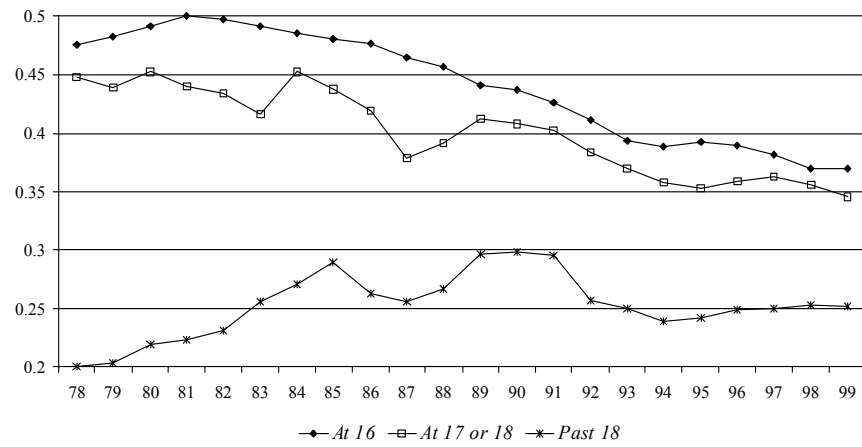
Source: FES data

Figure 2: Wage differentials associated with education 1978 to 1999



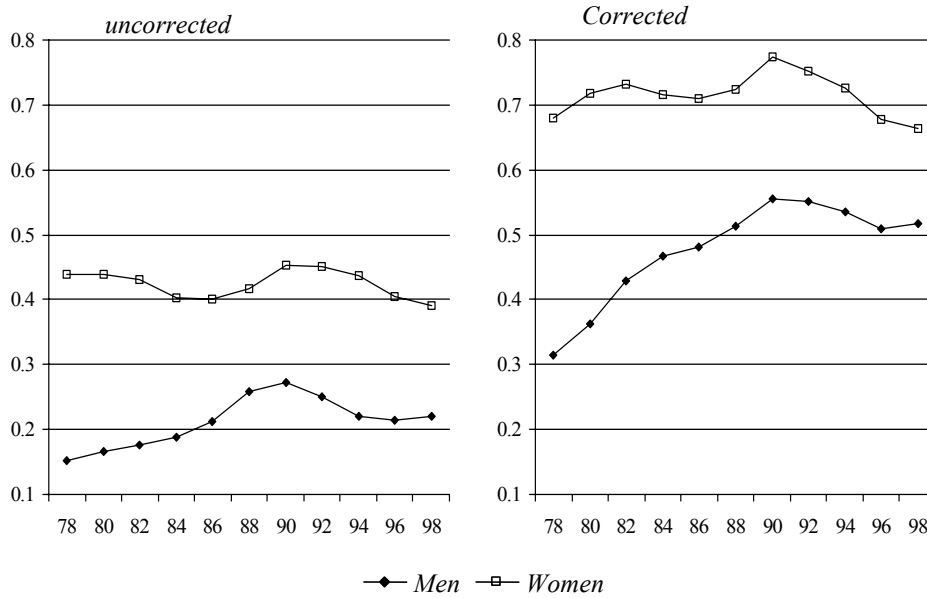
Graph plots regression coefficients on a dummy variable for having some form of post 18 education compared to a base of leaving school at or before 16

Figure 3: Gender wage differentials by age left full time education



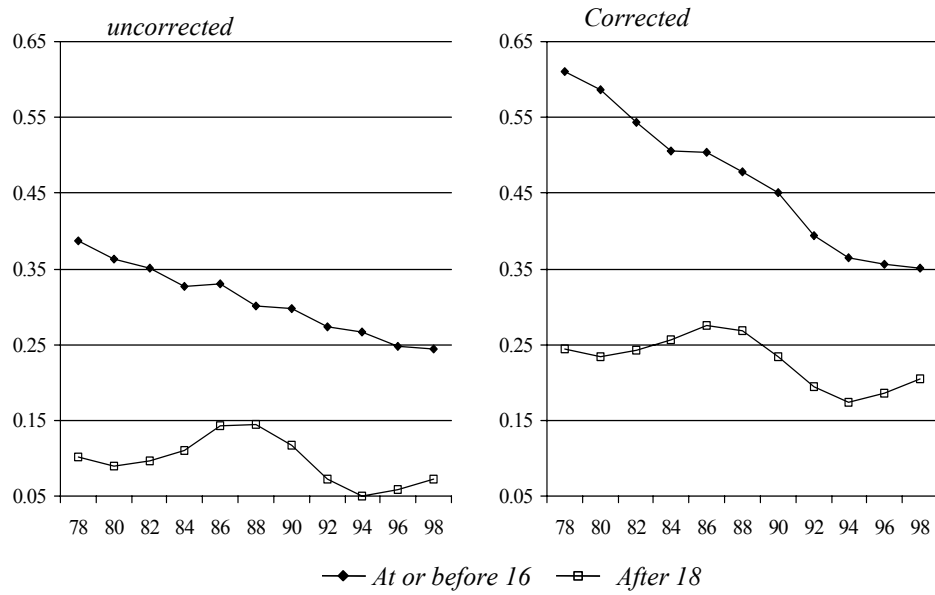
Graph plots regression coefficients on a dummy variable for being male

Figure 4: Wage differentials across education groups



Sample is all workers aged 23-28, right hand panel is corrected for selection. Difference between those leaving school after 18 and those at or before 16 is plotted

Figure 5: Wage differentials between men and women by age left full time education



Sample is all workers aged 23-28, right hand panel is corrected for selection.

Figure 6: exposition of simple education model

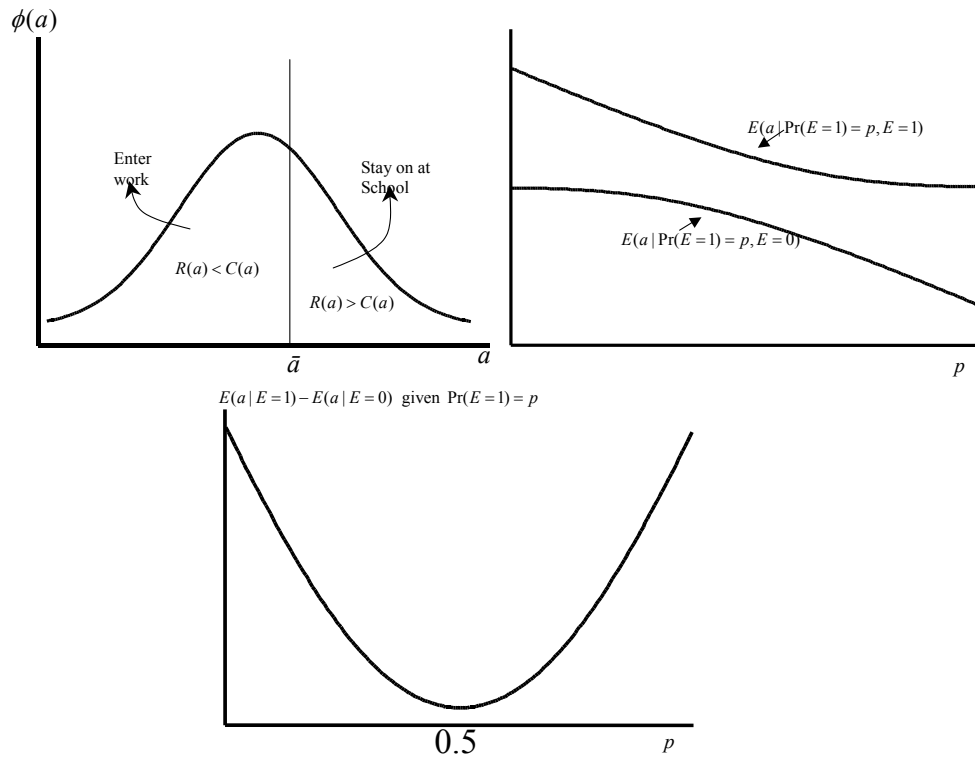


Figure 7: Estimated ability expectations from simple education model

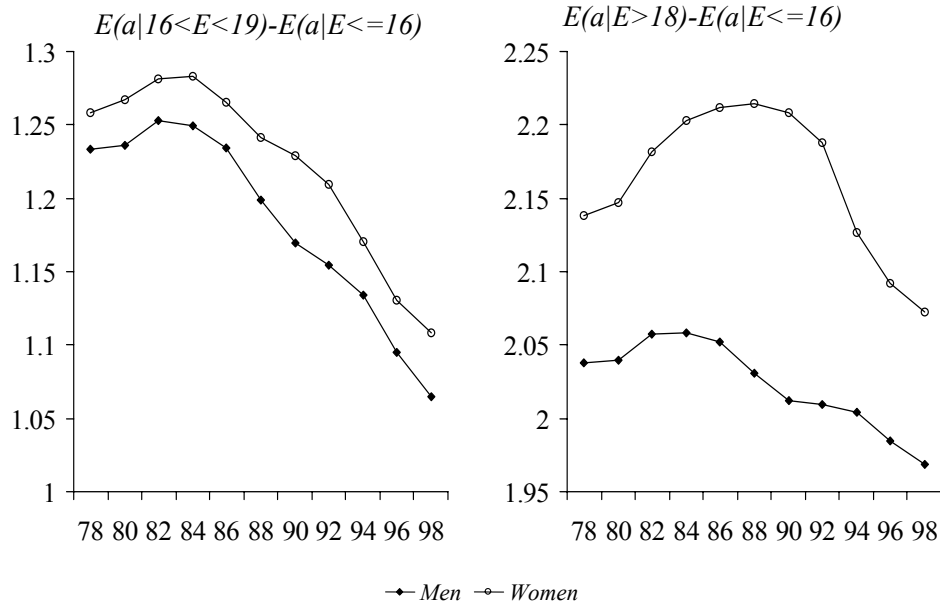


Figure 8: Proportions of 23-28 in the top two education groups

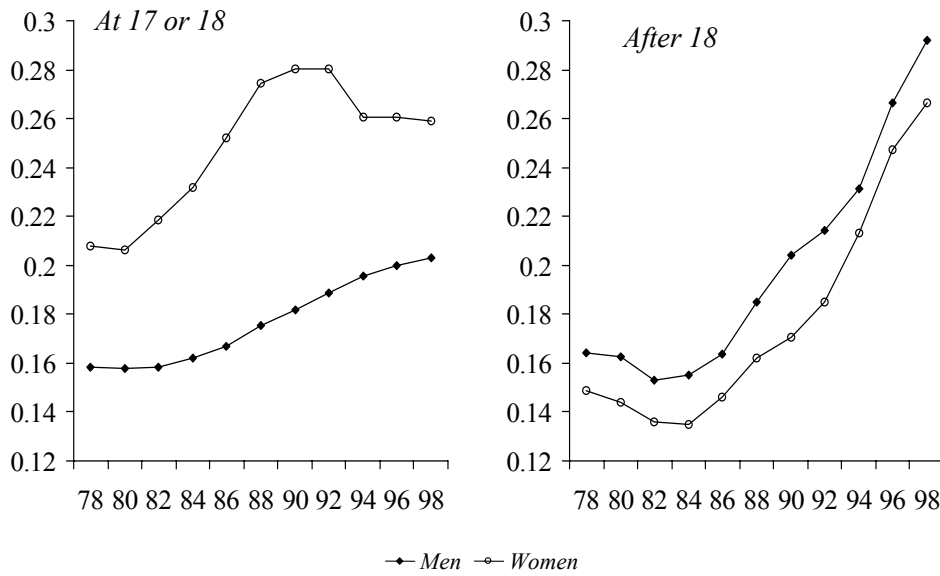
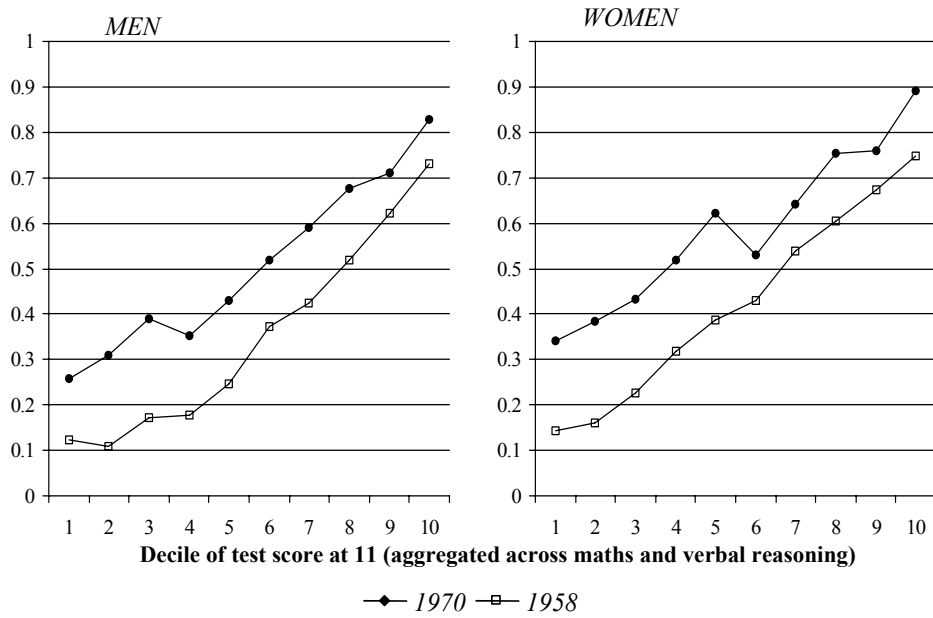
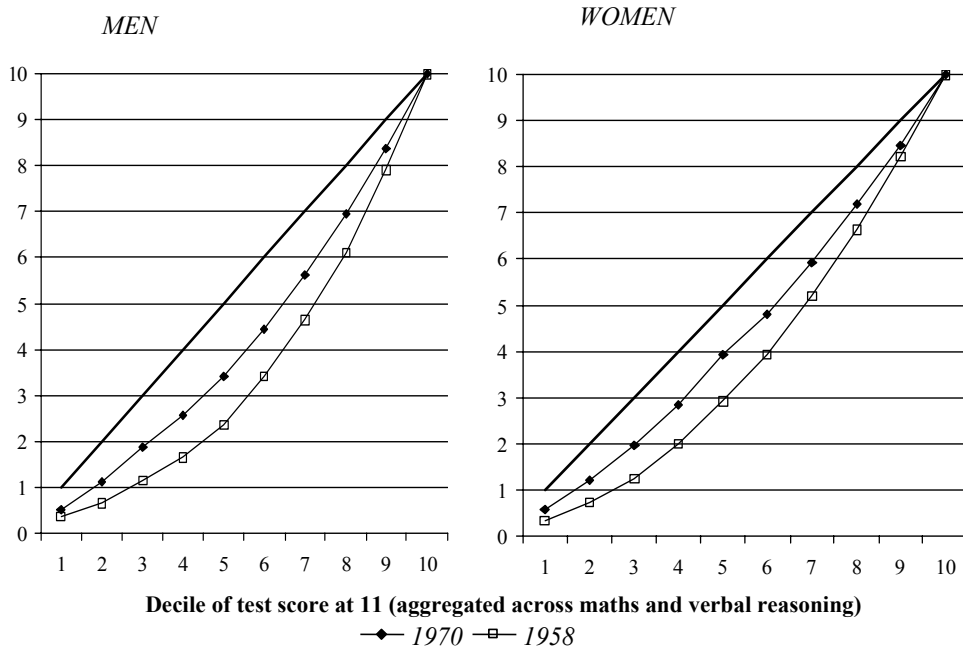


Figure 9: Proportions staying on at school past 16 by ability, gender and year of birth



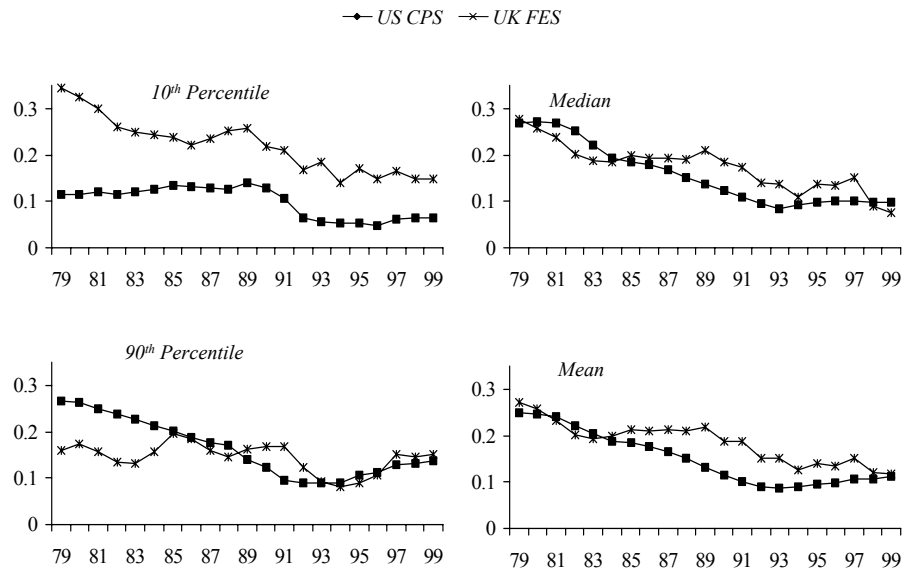
Source: NCDS (1958) and BCs70 (1970) data

Figure 10: Conditional distributions of test scores for those staying on at school past the age of 16



Source as in Figure 9

Figure 11: Gender wage differentials by percentile in the UK and the US



Source FES and CPS data, sample includes workers aged 23-28 inclusive