PSI Research Discussion Paper 3

Gender Discrimination in the Labour Market

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Gender Discrimination in the Labour Market

Evidence from the BHPS and EiB Surveys

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Abstract

This paper uses national survey data to measure the degree of gender discrimination in the UK labour market in the 1990s and compares this to results from earlier decades. It concludes that discrimination is still an important cause of the gender pay gap: women's pay would increase by about 10 per cent if they were rewarded in the labour market on the same basis as men. But this unequal treatment has declined since the 1980s, when equivalent figures were nearer 20 per cent. This decline in discrimination has been a more important cause of the reduction in gender pay differentials than women's relative increase in human capital.

Female part-timers experience a greater degree of discrimination than female full-timers: their pay would increase by about 15 per cent if their human capital attributes were remunerated in the same way as men's. As there is such a large difference between male and female part-timers, however, in their human capital endowments, discrimination explains proportionately less of the pay gap between male and female part-timers than it does between male and female full-timers.

Introduction

The gender pay gap is one of the most enduring labour market features, both in the UK and elsewhere. After narrowing to 69.7 per cent in 1977, female hourly pay as a percentage of male hourly pay did not reach 70 per cent until 1989 (New Earnings Survey). Although it has persisted into the 1990s, this decade has seen a steady erosion of the gender pay gap, which narrowed to 73 per cent in 1995. This improvement, however, has been more marked for female full-timers than female part-timers. Whereas female full-time hourly earnings as a proportion of male hourly earnings have risen from 77 per cent in 1989 to 81 per cent in 1995, female part-time hourly earnings as a proportion of male hourly earnings have risen only from 58 per cent to 60 per cent over the same period.

These developments suggest two research questions. Firstly, has the steady reduction in gender wage differentials in the 1990s been the result of a decline in gender discrimination in the labour market or of increased relative productivity on the part of women? Secondly, has the poorer progress made by female part-timers been associated with an increase in unequal treatment with regards to their remuneration, or is it related to their lower levels of productivity?

Human capital theory suggests that pay differences can be explained by differences in workers' endowments of 'human capital': investments in education, training and work experience which tend to increase pay because of their positive impact on productivity. An extensive empirical literature has developed in the UK to investigate the extent to which human capital variables can, in fact, explain pay variation in samples of employees. To the extent that human capital variables are unable to explain pay differences between men and women, the remainder of the pay differential has typically been taken as evidence of 'discrimination'. Virtually all UK studies which have explored this issue have produced some evidence of discrimination, but the extent to which discrimination explains the pay gap has varied quite considerably across studies. The existing literature is also largely confined to data collected in the 1970s and 1980s. The partial closure of the pay gap in the 1990s might be due to the increases in working women's human capital which have become evident during this decade (Paci and Joshi, 1996).

This paper uses two of the most important nationally representative datasets produced thus far in the 1990s, the British Household Panel Study (BHPS) and the Employment in Britain (EiB) survey, to investigate the research issues at hand. Using datasets from the early- to mid-1990s is appropriate because this is the period in which gender wage differentials were reduced and when the relative improvement in women's human capital became most readily apparent. They provide the ideal data, therefore, to examine whether discrimination is still an important cause of the gender pay gap and whether the reduction in gender wage differentials is due more to an improvement in women's human capital than to reduced discrimination. The data also enable us to investigate whether the experiences of part-time female workers differ from those of female full-timers.

This paper consists of five sections. The first examines the human capital theory of wage determination and explains how empirical analyses apply this theory to investigate the causes of gender wage differences. The second section summarises the findings of previous UK studies which have used this methodology. Some more detail on the data and econometric specification follows in the third section, while the fourth presents and discusses the empirical findings of the study. Conclusions are presented in the fifth section.

Theory and method

In its most basic form, neoclassical human capital theory suggests that, in a competitive labour market, wage rates will only differ between workers with different productivity-related endowments. These are factors such as education, work experience and training. More complicated formulations of the human capital approach, and labour market theorists from outside the neoclassical paradigm, have suggested a wider range of factors which determine pay, such as compensating differences, internal labour markets, monopoly and monopsony power, occupational segregation and labour market segmentation.[1]

This paper investigates the causes of gender wage differences by operationalising a simple human capital approach. This framework is adopted mainly to facilitate comparability with earlier studies. The human capital approach is summarised in the following wage equation:

1 An attempt to measure the importance of some of these factors in determining the gender pay gap is made in analyses reported elsewhere (Lissenburgh, 2001).

$$Ln\ wi = B_i X_i + e_i \tag{1}$$

where i equals either male or female workers; ln w is the natural logarithm of the hourly wage rate;[2] X is a vector of human capital attributes, B is a vector of parameters representing the impact of these attributes on pay, and e is a random error term.

The wage equation is estimated using Ordinary Least Squares (OLS) regression. The technique involves estimating the extent to which variation in the wage variable is associated with variation in the explanatory variables, which in this case are the human capital attributes. This technique is able to identify the independent impact of each of the explanatory variables on pay, holding constant the effect of the others.

This equation can be used to decompose the gender pay gap. Equations are typically estimated separately for men and women, reflecting the assumption that male and female pay structures are significantly different.[3] Once these equations have been estimated, the gender pay gap is decomposed using the Oaxaca-Blinder procedure (Oaxaca, 1973; Blinder, 1973). This procedure enables us to identify that proportion of the pay gap which is due to men's larger endowments of human capital, and that proportion which is due to men achieving higher returns on a given endowment of human capital. It is the latter component which is conventionally labelled 'discrimination'.

The formula used for the decomposition is as follows:-

$$Ln\ w_m - Ln\ w_f = B_m(X_m - X_f) + (B_m - B_f)X_f \tag{2}$$

where Ln wm – Ln w_f is the difference in the means of the logarithmic wages between men and women; X_m and X_f are the mean characteristics of men and women on the vector of human capital variables; and B_m and B_f are the corresponding vectors of coefficients. In this formulation, the $B_m(X_m - X_f)$ term captures the contribution to the wage difference arising from differences in average human capital attributes between men and women. It measures the wage differential which would persist if women were paid according to the male pay structure but with their given stock of human capital endowments. The (Bm – Bf)Xf term measures differences in the remuneration of human

2 Using the natural logarithm of the wage variable increases the efficiency of estimation because it increases the extent to which the variable approximates to a Gaussian distribution. It also enables the coefficients to be interpreted as approximate elasticities.

3 Where a joint equation is fitted, the slope coefficients of explanatory variables are constrained to be the same for both sexes. It is, of course, possible to test whether gender-based pay structures are different by performing Chow tests on the male and female equations. This is the procedure adopted in this paper.

capital attributes and thus indicates the contribution of 'discrimination' to the gender pay gap.

It is customary for the results of the decomposition to be used in the calculation of a 'discrimination coefficient'. This is computed as follows:

$$D_f = \{exp[(B_m - B_f)X_f] -1\} \times 100 \qquad (3)$$

D_f can be interpreted as the percentage increase in pay that women would receive, given their stock of human capital attributes, if they were remunerated according to the male pay structure. It represents, therefore, the increase in women's pay which would occur if discrimination were eliminated.[4]

The measure cannot, therefore, be considered either an upper or lower bound estimate of gender discrimination.

Limiting the range of factors which are considered to affect pay to a narrow range of human capital variables can be seen to produce an upper bound estimate of discrimination, in that a number of potentially important variables, such as occupation and industry, are excluded. This reflects the assumption that occupational attainment, for example, might be in part an outcome of discrimination. To the extent that it is, rather, the result of individual choice, this methodology will produce inaccurately high measures of discrimination. Conversely, the inclusion of education and work experience as determinants of pay assumes that these are exogenous in the model, whereas expectations of, for example, low returns to qualifications, might have discouraged women from acquiring these. To this extent, the methodology will produce lower bound estimates.

There are other caveats which must be applied before Df can be accepted as a measure of discrimination. The wage equations from which it is derived are based only on measurable indicators of productivity. In reality, factors such as motivation and ambition are likely to have an impact on an individual's performance in the labour market as well. If there are systematic differences between men and women in relation to these unobserved factors, the discrimination coefficient may be inaccurate. Again, however, it is very difficult to make an a priori judgement about whether they would have an upwards or downwards effect. Some attempt can be made to deal with

4 The Oaxaca decomposition and calculation of the discrimination coefficient can be carried out using the male human capital attributes as the standardising factor. As a result of the index number problem (Cotton, 1988), this method and indeed other alternatives (Oaxaca and Ransom, 1994) can produce markedly different estimates of discrimination. As there is no objective criterion by which the efficacy of these alternative methods can be judged, we maximise comparability by using the customary approach of standardising according to the female human capital attributes.

unobserved heterogeneity using the Heckman correction for sample selection bias, although its ability to solve this problem is only partial. This correction is discussed in more detail in section three of this paper.

Previous estimates

A considerable number of studies have estimated gender discrimination in the UK labour market using a methodology similar to that described above. A selection of these studies is summarised in Table 1.[5]

Table 1: *Summary of studies estimating gender discrimination*

Author and date of publication	*Data source*	*Discrimination coefficient (Df)*
Greenhalgh (1980)	General Household Survey, 1971 and 1975	Single, 1971=24% Single, 1975=10%
Zabalza and Arrufat (1985)	General Household Survey, 1975	Married=6%
Joshi and Newell (1987)	National Survey of Health and Development, 1972 and 1977	1972=51% 1977=32%
Miller (1987)	General Household Survey, 1980	15%
Wright and Ermisch (1991)	Women and Employment Survey, 1980	Married=21%
Paci and Joshi (1996)	National Child Development Survey, 1991	24%

Studies of the 1970s

The studies which used data from the 1970s suggested that gender discrimination declined after the implementation of the Equal Pay Act in 1975. Greenhalgh's (1980) analysis of the General Household Survey (GHS) suggested that single women's pay would have been 24 per cent higher in the absence of discrimination in 1971, but only 10 per cent higher in 1975.

5 We have concentrated on those studies which have used nationally representative data and parsimonious wage models which are largely restricted to human capital variables. There is, of course, a wide range of studies which have examined gender discrimination amongst particular groups of workers, such as professionals (Chiplin and Sloane, 1976), graduates (Dolton and Makepeace, 1986) and workers in a particular establishment (Siebert and Sloane, 1981). Some of those studies which have used more comprehensive wage models (Elliott, Sandy and Sloane, 1993; Sloane, 1994; Harkness, 1996) are examined in work to be published shortly (Lissenburgh, 2001).

Zabalza and Arrufat (1985) suggested an even greater erosion of discrimination, producing a discrimination coefficient of only 6 per cent.

These studies have been subjected to a number of criticisms. Firstly, the GHS does not contain work history data, so these studies were forced to use 'potential work experience' or 'imputed work experience' in their wage equations. The use of these techniques makes the measure of Df particularly sensitive to the specification of the equation. Certainly Zabalza and Arrufat's (1985) very low estimate is strongly related to their inclusion of an imputed measure of time out of the labour market, which accounts for over 70 per cent of the wage differential. Secondly, they make comparisons between either single men and single women or married men and married women. The justification for the former approach is that single women are 'more like' men than married women because they have similar motivations and work histories. As well as being out-dated, this approach ignores the fact that what is at issue is the amount of discrimination against women in general, regardless of whether they are married or unmarried (Dolton and Makepeace, 1986). The studies which compare only married men to married women are subject to the same criticism.

Joshi and Newell's (1987) analysis of the National Survey of Health and Development (NSHD) overcomes these limitations. It uses data on actual work experience and presents models comparing all men to all women. The main conclusion of the study is consistent, however, with those produced by earlier studies using data from the 1970s, in that the discrimination coefficient is seen to fall from 51 per cent in 1972, before the implementation of the Equal Pay Act, to 32 per cent in 1977, after the Act's introduction. The Df measures are relatively high. This is somewhat surprising given that the study used a cohort survey, where the respondents were 26 years old in 1972 and 32 years old in 1977. As they exclude women who would have spent many years working when there were was no equal opportunities legislation, one would perhaps expect comparisons of young men and young women to produce lower discrimination estimates than those using nationally representative probability samples (such as the GHS). Nevertheless, the strengths of Joshi and Newell's (1987) study compared to earlier analyses mean that it presents the most acceptable benchmarks for the degree of labour market gender discrimination in the 1970s.

Studies of the 1980s

Studies which used nationally representative data from the early 1980s provide some evidence of a further decline in discrimination. Miller's (1987) analysis of the 1980 GHS produces a discrimination coefficient of 15 per cent. This study is subject to the same criticism made of earlier studies based on the GHS, in that data on actual work experience were not available. However, Wright and Ermisch's (1991) analysis of the Women and Employment Survey (WES), for which work history data were available, provides estimates for married women compared to married men which are only slightly higher (21 per cent). This study can again be criticised on the grounds that its findings are only applicable to the married population, but data on men in the WES were restricted to the spouses of female respondents. In a later study using the same data, Ermisch and Wright (1992) find that their wage models for all working women are similar to those for married women, so their Df estimate can probably be generalised.

The 1990s

Paci and Joshi's (1996) analysis of the 1991 National Child Development Study (NCDS) is the only published study which has estimated the extent of discrimination using 1990s data and a parsimonious human capital specification which affords comparison with the previous literature.[6] Their analysis of a nationally representative cohort of 33 year olds suggests that women's pay would be 24 per cent higher in the absence of discrimination. Although this figure is higher than that produced for 1980 by Miller (1987) and Wright and Ermisch (1991), it is most appropriately compared to the figure of 32 per cent which Joshi and Newell (1987) calculated for 32 year olds in 1977. This suggests that discrimination declined gradually over the 1980s, but that it remains a significant feature of the labour market.

Of the studies summarised in Table 1, only Paci and Joshi (1996) calculate a discrimination coefficient while allowing the returns to human capital to differ between women in full-time and part-time work. Ermisch and Wright (1992) and Harkness (1996) suggest that women's returns to human capital do differ according to working time, so this is an appropriate alteration to the basic methodology. For the purposes of analysing gender discrimination in the 1990s, however, Paci and Joshi (1996) are confined to using data from very early in the decade and which are not drawn from a nationally representative probability sample of the whole population. This limits the extent to which their findings can be generalised.

6 The human capital specification used by Harkness (1996) does not include work experience variables, while Paci, Joshi and Makepeace (1995) cover similar material to Paci and Joshi (1996).

Data and econometric specification

Data from the British Household Panel Survey (BHPS) and the Employment in Britain (EiB) survey are used for the analyses conducted in this paper. The BHPS and EiB datasets are well suited for this purpose. The BHPS is a longitudinal dataset containing information on representative UK households. This paper uses data from the first four waves of the BHPS, covering the period 1991–95. The EiB survey was carried out in 1992 and collected data from a nationally representative probability sample. It is a cross-sectional survey which, like the BHPS, contains detailed work history sections which give the data an important longitudinal element.

For the purposes of this paper, parsimonious wage equations, analogous to equation (1), are computed separately for men and women.[7] The measures of human capital which are used as independent variables in the wages models include years of full-time work experience, years of part-time work experience and time spent out of employment.[8] Each of these variables is entered in quadratic as well as linear format. We enter full-time and part-time employment separately to allow the remuneration of these two types of human capital investment to vary in the models. We follow Wright and Ermisch (1991) by including the measure of non-employment, in order to allow for the effect of depreciating human capital.

Other variables include qualifications, dichotomous variables for age in order to capture birth cohort effects on earnings (Meghir and Whitehouse, 1996), regional dummy variables and a dummy for part-time working, in order to control for any intercept shifts associated with this. The effect of part-time working is then explored more systematically by running separate models for female full-timers and female part-timers.

While they are included in the models, time in part-time employment and time out of the labour market are treated somewhat differently from the other variables in the decomposition of the gender pay gap. Although years of part-time employment and years of non-employment are included in the male

7 Chow tests for structural stability confirmed that the parameters in the male equations were significantly different from those in the female equations.

8 Work history information dating back to the respondent's first entry onto the labour market was only collected at Wave Two of the BHPS but work history variables were also constructed for the Wave One analyses. This was done by using the 'job history' sections, which are collected at each wave of the survey and which detail the activities of the respondent that have taken place since September of the previous year. Where Wave One respondents also appeared in Wave Two, we used the annual job history information collected at Wave Two, along with the lifetime work history, to work backwards and calculate the respondent's quantities of full-time work experience, part-time work experience and time out of the labour market at Wave One.

equations, it would be invalid to treat differences in male and female coefficients on these variables as evidence of discrimination. This is because the variables are measuring different things for men and women. In the case of non-employment, this is usually spent looking after children for women but as unemployment for men. Part-time employment is similarly associated with childcare for women but very little is known about the reasons for male part-time employment. In contrast, men's and women's motivations for undertaking full-time employment are very similar (Burchell and Rubery, 1994). In order to take account of these differences, the effect on the pay gap of time in part-time employment and time in non-employment is given a separate category in the decomposition. This is called 'social reproduction', in view of the fact that the pronounced mean differences between women and men on these variables arise principally because of women's greater responsibility for childrearing. This category records the effect on the gender pay gap of both mean differences and coefficient differences relating to years of part-time employment and time out of the labour market.

The effects of mean differences in full-time experience, however, are treated as differences in human capital endowments and gender differences in the coefficients on full-time experience are taken as evidence of discrimination. The other variables mentioned above are treated likewise. This approach of making a distinction between part-time employment, non-employment and other variables is similar to that taken by earlier research (Wright and Ermisch, 1991; Ermisch and Wright, 1992) and so facilitates comparability.

The wage models also include a correction term for sample selection bias associated with the work participation decision. The problem of sample selection bias arises because workers who are participating in the workforce at any one time may be a non-random subset of all potential labour force participants. If this is the case, the OLS estimates produced by a wages model such as equation (1) will be biased and inconsistent. This type of sample selection bias can be eliminated by using the Heckman (1979) procedure. This involves constructing a probit model of the determinants of work participation and deriving a variable, LAMBDA, which reflects the unmeasured characteristics which encourage participation in paid work. Including this variable in the wage equation then takes account of unobserved heterogeneity within the working sample, associated perhaps with amorphous characteristics such as motivation and ambitions about employment and careers, which encourage work participation (Dex, Walters and Alden, 1993). Inclusion of the LAMBDA variable thus ensures that the coefficients produced by the wages models are unbiased and consistent, which increases the reliability of the findings. While correcting for sample selection bias in this way has become a standard procedure in empirical analyses of earnings, we depart from the norm in performing the correction for male as well as female wage models. This is made necessary by the large proportions of male workers observed in non-employment in the surveys. Like the 'social reproduction' variables, the effect of sample selection is shown separately in the decompositions.

RESULTS

The male and female wage models

Appendix Tables 1 to 5 show the results of the male and female wage models.[9] The models are well specified, with a large majority of independent variables being statistically significant in each case. While none of the models is able to account for more than half of pay variation, the adjusted R levels of 0.36–0.44 are satisfactory given the parsimonious specification. The signs and significance levels of individual variables are very much in accordance with the findings of previous research and theoretical expectations. Wages are positively related to qualification level, with most of the models showing that even having CSE as a highest qualification raises pay relative to having no qualifications. The returns to qualifications tend to become higher with each step up the hierarchy. Wages also tend to rise with seniority, although the degree of linearity is less pronounced. This provides some support for the contentions of Meghir and Whitehouse (1996) regarding the existence of birth cohort effects on earnings.

The relationship between wages and full-time work experience conforms to expectations in that it is quadratic. The effect of part-time work experience on wages also follows a consistent pattern but is u-shaped in eight of the ten models. This means that pay falls with part-time experience but then rises once part-time experience reaches a certain level. This suggests perhaps that there are returns on work experience in stable part-time jobs but not in short-term ones. These findings on the effect of part-time work experience on pay are consistent with those produced by Harkness (1996) in more comprehensive specifications using Wave 2 of the BHPS, but have rarely been found elsewhere. Part-time experience is more commonly found to have no effect on pay (Payne, Casey, Payne and Connolly, 1996). Time out of employment affects pay in a similar way, with the linear term having a negative sign and the quadratic having a positive one. Unlike part-time experience, however, the negative effect is usually larger than the positive one so that, overall, time out of the labour market has a negative effect on pay. This relationship applies

9 Definitions of the variables used in the models are given in Appendix Table 11.

for both men and women. Wright and Ermisch (1991) found similar results for women.

The intercept dummy for part-time working in the current job has a negative and significant effect on pay in all of the female models but in only one of the male models. With so few men working part-time, the variable has little scope to affect pay in the male equations. Its negativity in the female equations is consistent with the results of an extensive empirical literature (Waldfogel, 1995; Lissenburgh, 1996).

The LAMBDA variable, reflecting unobserved heterogeneity associated with work participation, is negative and significant in four of the ten models.[10] This result only occurs in the BHPS and is more common for women than men. The LAMBDA variable is non-significant in the other models. Where a finding of negative selectivity is produced, this means that respondents possessing unmeasured attributes which enhance their earnings are less likely to be employed at the time of the survey.

Considerable attention has in the recent past been focused on the interpretation of sample selection effects (Dolton and Makepeace, 1987; Ermisch and Wright, 1994). A finding of negative selectivity has sometimes been dismissed as being a result of mis-specification. This is because of the a priori expectation that respondents will be encouraged into work because of some employment advantage such as motivation or ambition. Ermisch and Wright (1994) have argued, however, that, at least for women, negative selectivity is consistent with Heckman's (1974) 'shadow prices' model of labour supply. This is because a woman's reservation wage is likely to have a relatively high positive correlation with her potential earnings, due to women who are more productive in jobs also tending to be more productive in home activities. As it is assumed, according to this line of argument, that women with a high unmeasured tendency to enter work must have a low reservation wage, this renders negative selectivity plausible.

Decomposition of the gender pay gap

The wage models were used to decompose the pay gap with the formula in equation (2). Table 2 contains the results of the decomposition.

10 The work participation models contained variables on age, education, health, attitudes towards gender roles, age of youngest child, number of children, marital status, number of others employed in the household and region. The selection equation also contained work experience variables, to guard against confounding their effects on wages with their effects on sample selection (Ermisch and Wright, 1992).

Table 2: *Decomposition of the gender pay gap*

		BHPS			
Component	*EiB*	*Wave 1*	*Wave 2*	*Wave 3*	*Wave 4*
Human capital attributes	0.087 (33%)	0.062 (20%)	0.125 (43%)	0.136 (48%)	0.132 (45%)
Social reproduction	0.062 (23%)	0.156 (50%)	0.075 (26%)	0.067 (24%)	0.065 (22%)
Discrimination	0.148 (56%)	0.098 (31%)	0.089 (31%)	0.054 (19%)	0.074 (25%)
Sample selection	0.032 (–12%)	0.002 (–1%)	0.004 (1%)	0.028 (10%)	0.021 (7%)
Log wage gap	0.265	0.314	0.292	0.285	0.293
D_f	16%	10.3%	9.3%	5.6%	7.7%

Human capital attributes

The first row of figures in Table 2 shows the logarithmic wage differential due to mean differences in human capital attributes between men and women. The EiB data, for example, show that if women had the same mean human capital attributes as men their log-pay would increase by 0.087 (9 per cent).[11] This differential is due to the fact that, on average, women's stock of human capital attributes is smaller than that of men. In the EiB sample, for instance, working men have an average of 18 years' full-time work experience, compared to 11 years in the case of working women. Similarly, whereas 24 per cent of working men in the EiB sample have qualifications above 'A' Level, this is true of only 16 per cent of working women. Overall, mean differences in human capital attributes can be seen to account for a third of the pay gap according to the EiB analyses. With the exception of the first wave, the BHPS models suggest that a larger proportion of the pay gap is due to human capital differences. Taking an average across the five models, almost two-fifths (38 per cent) of the pay gap can be attributed to gender differences in human capital endowments.

Given the considerable progress which women have made in recent decades in closing the human capital gap, it is surprising to note that this proportion is larger than existed in the early 1980s. In Wright and Ermisch's (1991) favoured specification, attributes accounted for only 17 per cent of the pay gap. There are two explanations for this seeming anomaly.

11 Log pay differentials are converted into percentages by taking the antilog, subtracting 1 and multiplying by 100.

Firstly, the relative advances made by women in acquiring qualifications and maintaining continuity of full-time work experience have been uneven. They have been made principally by the younger birth cohorts (Paci and Joshi, 1996) and by women at higher levels of the occupational hierarchy (McRae, 1993; Dex, Joshi and Macran, 1996). In nationally representative probability samples of the whole population, these groups of women do not predominate and their experiences do not accurately reflect those of the majority of women. It is notable, for example, that working women in the 1980 WES averaged just under 11 years' full-time work experience, only marginally below the 11 years of EiB working women and about the same as working women at the first wave of the BHPS.

Secondly, human capital attributes are rewarded more substantially in percentage terms in the labour market of the 1990s than they were in the labour market of the early 1980s. Whereas, for example, the spouses of WES respondents who had qualifications above 'A' Level earned a 66 per cent premium over men with no qualifications (Wright and Ermisch, 1991), men with qualifications above 'A' Level but below degree level earned a 77 per cent premium averaged over our five models, while those with a degree earned 115 per cent more, after controlling for other variables, than men with no qualifications. As the decomposition calculates the contribution of attributes by multiplying gender mean differences by the male coefficients, it can be seen how the increase in coefficients will boost the contribution of attributes to the pay gap, even if there has been little change in the mean differences. The economic background to this statistical development is the growth in wage inequality in the labour market which has occurred since the late 1970s, with skilled workers experiencing much faster wage growth than the unskilled (Machin, 1996).

Social reproduction

The second row in Table 2 shows the contribution of 'social reproduction' variables to gender wage differentials. These variables are designed to capture women's greater responsibility for childrearing. The datasets show a consistent pattern here, with four out of the five suggesting that social reproduction variables account for about a quarter (22–26 per cent) of the pay gap. These figures are very similar to the 25 per cent reported by Wright and Ermisch (1991) for the 1980 WES. As with human capital attributes, these variables show a somewhat surprising persistence in their ability to explain the pay gap, especially given the reductions in women's labour market interruptions around childbirth (McRae, 1991; Callender, Millward, Lissenburgh and

Forth, 1997). Again, however, this can be partly explained by the bifurcation of women's labour market experiences in relation to these factors (Macran, Joshi and Dex, 1996).

Discrimination

The third row in Table 2 shows the contribution of discrimination to the gender pay gap. In the BHPS models, the contribution of discrimination varies from about a fifth to about a third (19–31 per cent). A drift downwards can be observed from the first and second to the third wave, which coincides with a reduction in the observed wage gap, but the contribution rises again in the fourth wave. Discrimination is more important as an explanation of the pay gap in the EiB models, accounting for over half (56 per cent) of the differential. The fifth row expresses these contributions in the Df format, which shows the percentage increase in women's pay which would occur if women were remunerated for their human capital in the same way as men. The discrimination coefficient varies from 6–10 per cent across the BHPS waves and is higher, at 16 per cent, for the EiB computations. The average across the five datasets is just under 10 per cent.

Even the relatively high EiB estimate of 16 per cent is lower than Wright and Ermisch's (1991) favoured estimate of 21 per cent. The proportion of the pay gap explained by discrimination in our analyses, which averages about a third (32 per cent) across the five datasets, is correspondingly lower than the 48 per cent it contributed in the 1980 WES. This can be taken as evidence that the steady drift downwards in discrimination which Wright and Ermisch (1991) noted from the early 1970s to the early 1980s, and which Paci and Joshi (1996) have found in cohort studies, has continued from the early 1980s to the mid-1990s. Nevertheless, our analyses confirm that women's pay is still depressed by discrimination in the 1990s and that this unequal treatment accounts for a substantial portion of the pay gap.

The wage models for female full-timers and female part-timers

The results discussed so far afford comparability with earlier research which has looked at overall differences between men and women. But given the different experiences of women working full-time and part-time with regard to gender wage differentials in recent years, it is necessary to allow the returns to human capital to vary according to whether a woman is working full-time or part-time. This can be done by running separate wage models for women in full-time and part-time employment.[12]

Appendix Tables 6 to 10 show the variables and coefficients relating to this second set of models. The same independent variables were used as in the earlier models, except that the part-time dummy variable was dropped. The female full-time models are very similar to those for working women as a whole. The amount of pay variation accounted for by the models (adjusted R measures of 0.37–0.45), and the signs and significance of coefficients follow the same pattern as the female models.

This is not the case, however, with the female part-time models. These explain much less of the pay variation amongst female part-timers (adjusted R measures of 0.19–0.28) and a smaller proportion of the independent variables have a significant impact on pay. This is particularly the case among the work history variables, where the measures of part-time experience and time out of the labour market often have no effect. The tendency for female part-time wage models to explain less pay variation than those for men and female full-timers accords with much previous literature (Ermisch and Wright, 1988; Harkness, 1996) and can be explained by the relative homogeneity of female part-time employment in terms of the range of occupations represented.

Despite this limitation, the female part-time wage models follow a similar basic pattern to that shown by other models. There are positive and significant returns to education, and evidence of birth cohort effects. It is possible to use the models, therefore, along with those for female full-timers, to decompose the wage differentials between male and female full-timers on the one hand, and male and female part-timers on the other.

Decomposition of the gender pay gap: differences by working time

Table 3 summarises the results of this exercise. The figures in Table 3 are averages across the five datasets. The decomposition based on all working men and women is included for comparative purposes.

12 As was the case with the comparison between men and women, Chow tests confirmed that there was a significant difference between the female full-time and female part-time pay structures, thus providing a technical justification for the computation of separate models.

Table 3: *Decomposition of the gender pay gap: comparisons*

Component	*Men/women*	*Men/FT women*	*Men/PT women*[13]
Human capital attributes	0.108 (37%)	0.063 (32%)	0.184 (41%)
Social reproduction	0.086 (30%)	0.041 (21%)	0.119 (27%)
Discrimination	0.093 (32%)	0.090 (46%)	0.132 (30%)
Sample selection	0.004 (1%)	0.003 (2%)	0.011 (2%)
Log wage gap	0.291	0.197	0.446
D_f	9.8%	9.5%	15.2%

Human capital attributes

Human capital attributes are less important as determinants of the pay gap between male and female full-timers than between male and female part-timers. The first row of figures in Table 3 suggests that, if female full-timers had the same human capital attributes as men, their log-pay would increase by 0.063 (7 per cent). Female part-timers would stand to gain much more, however, from closing the attribute gap with men. Their log-pay would increase by 0.184 (20 per cent) if they had the same human capital endowments as men. Mean human capital attribute differences are correspondingly more important as a proportion of the male/female part-time wage gap, accounting for 41 per cent as against 32 per cent of the male/female full-time differential. These findings are consistent with previous empirical literature, which has noted wide skill differences between female full-timers and female part-timers in relation to the kinds of conventional measures we are using (Horrell, Rubery and Burchell, 1990; Gallie, 1991).

Social reproduction

The finding that social reproduction variables explain more of the pay gap between male and female part-timers than between male and female full-timers is also consistent with expectations. Having responsibility for childcare is one of the main reasons women do part-time work and female part-time workers are also more likely than female full-timers to have had time out of the labour market.

13 The male models used for this exercise were identical to those used for the comparison between men and women, except that the part-time dummy variable was dropped from the equation. This caused very little change in the models, so they are not reported.

Discrimination

The findings on discrimination are of particular interest. Women in full-time jobs would see their log-pay increase by 0.09 (9.5 per cent) if their human capital attributes were remunerated in the same way as men's, while female part-timers' log-pay would increase by 0.132 (15.2 per cent) on the same basis of comparison. These findings suggest that a particularly high degree of discrimination against female part-timers is partly responsible for their inability to join female full-timers in closing the pay gap with men in the 1990s. As the log wage differential between male and female part-timers is so large, however, discrimination only accounts for 30 per cent of this differential, whereas it accounts for 46 per cent of the much smaller pay gap between male and female full-timers. Thus, while female part-timers stand to gain more from equal treatment, unequal treatment is of greater relative importance for female full-timers as an explanation of why they earn less than men. For female part-timers, the human capital attribute gap explains more of the pay gap (41 per cent) than discrimination (30 per cent). The opposite is the case for female full-timers, for whom discrimination explains almost half of the pay gap (46 per cent), whereas a shortfall of human capital accounts for only a third (32 per cent).

Conclusions

The analyses in this paper are able to answer the two research questions posited in the introduction. Firstly, the decline in gender wage differentials which has occurred since the mid-1980s is due more to a decline in gender discrimination than to a relative improvement in women's stock of human capital. Secondly, while female part-timers would gain more from equal treatment than female full-timers, the relatively large gender pay gap faced by female part-timers is explained more by a lack of human capital than by discrimination.

Analyses which compare men with women suggest that women's pay would increase by about 10 per cent if their human capital were remunerated at the same rate as men's. This is quite a substantial drop from the 21 per cent estimate produced by the most comparable analysis using nationally representative data from the early 1980s (Wright and Ermisch, 1991). Comparisons with this study also suggest that discrimination explains a smaller proportion of the pay gap than was the case in the early 1980s, and gender differences in human capital endowments explain more.

These findings are only partly consistent with similar studies which have used cohort data. While finding a similar tendency for discrimination coefficients to fall from 32 per cent for a sample of 32 year olds in 1977 to 24 per cent among a sample of 33 year olds in 1991, Paci and Joshi (1996) find that the fall in the gender pay gap over the period is explained more by women closing the human capital shortfall than by a reduction in discrimination. The reason for this difference is that the relative improvement in women's human capital has been experienced more substantially by younger birth cohorts than by the female labour force as a whole. As these cohorts start to make up a larger proportion of the female labour force and are joined by younger women whose human capital is in many ways superior to that of their male contemporaries, analyses of nationally representative datasets such as the BHPS should reveal a decreasing proportion of the pay gap being due to human capital differences.

Female part-timers did not experience the same relative increase in their pay as enjoyed by female full-timers from the mid-1980s onwards. This is partly due to their experiencing a more pronounced degree of discrimination than that to which female full-timers are subject. In percentage terms, however, discrimination is less important as an explanator of the male/female part-time pay gap than of the male/female full-time pay gap, and human capital differences explain more of the differential between male and female part-timers than does discrimination. These findings are consistent with those produced by Harkness (1996) in analyses of the BHPS, which used more comprehensive wage models.

While women's experience of unequal treatment in the labour market would appear to have declined, discrimination is still a long way from being eliminated. An important issue which remains is what policy instruments might be able to make further inroads into the gender pay gap. The analyses in this paper have been geared toward estimating a general indicator of the degree of discrimination, but they provide little insight into the processes by which discrimination comes about and thus tell us little about how it can be reduced. These issues are tackled in later work (Lissenburgh, 2001).

References

Blinder, A (1973) 'Wage discrimination: reduced form and structural estimates'. *Journal of Human Resources*, Fall, 436–55

Burchell, B and J Rubery (1994) 'Divided women: labour market segmentation and gender segregation' *Gender segregation and social change* A Scott. Oxford: Oxford University Press, 80–120

Callender, C, N Millward, S Lissenburgh and J Forth (1997) *Maternity Rights in Britain, 1996*. London: Policy Studies Institute

Chiplin, B and P Sloane (1976) 'Personal Characteristics and Sex Differentials in Professional Employment'. *Economic Journal*, Vol 86, 729–45

Cotton, J (1988) 'On the Decomposition of Wage Differentials'. *Review of Economics and Statistics*, Vol 70, No 2, 236–43

Dex, S (1985) *The Sexual Division of Work*. Brighton: Wheatsheaf

Dex, S, H oshi and S Macran (1996) 'A widening gulf among Britain's mothers'. *Oxford Review of Economic Policy*, Vol 12, No 1, 65–75

Dex, S, P Walters and D Alden (1993) *French and British Mothers at Work*. Basingstoke: Macmillan

Dolton, P and G Makepeace (1986) 'Sample Selection and Male-Female Earnings Differentials in the Graduate Labour Market'. *Oxford Economic Papers*, No 38, 317–41

Dolton, P and G Makepeace (1987) 'Marital Status, Child Rearing and Earnings Differentials in the Labour Market'. *Economic Journal*, Vol 97, 897–922

Elliot, R, R Sandy and P Sloane (1993) *Compensating differences, discrimination and male/female earnings differences*. University of Aberdeen Department of Economics Discussion Paper No 93–06

Ermisch, J and RWright (1992) 'Differential Returns to Human Capital in Full-time and Part-time Employment'. *Issues in Contemporary Economics* N Folbre, B Bergmann, B Agarwal and M Floro. Basingstoke: Macmillan, 195–212

Gallie, D (1991) 'Patterns of Skill Change : Upskilling, Deskilling or the Polarization of Skills?'. *Work, Employment and Society* Vol 5, No 3, 319–351

Greenhalgh, C (1980) 'Male-Female Differentials in Great Britain: Is Marriage an Equal Opportunity?'. *Economic Journal*, Vol 90, 751–75

Harkness, S (1996) 'The Gender Earnings Gap: Evidence from the UK'. *Fiscal Studies*, Vol 17, No 2, 1–36

Heckman, J (1974) 'Shadow prices, market wages and labour supply'. *Econometrica*, Vol 42, 679–94

Heckman, J (1979) 'Sample selection bias as a specification error'. *Econometrica*, Vol 47, 153–161

Horrell, S, J Rubery and B Burchell (1990) 'Gender and Skills'. *Work, Employment and Society* Vol 4, No 2, 189–216

Joshi, H (1986) 'Participation in paid work: evidence from the Women and Employment Survey'. *Unemployment, search and labour supply* R Blundell and I Walker Cambridge: Cambridge University Press, 217–42

Joshi, H and M Newell (1987) 'Pay differences between men and women: longitudinal evidence from the 1946 birth cohort'. *Centre for Economic Policy Research Discussion Paper* No 156

Lissenburgh, S (1996) *Value for money: the costs and benefits of giving part-time workers equal rights* London: Trades Union Congress

Lissenburgh, S (2001) *Causes of the gender pay gap in the 1990s*. London: Policy Studies Institute (forthcoming)

McRae, S (1991) *Maternity Rights in Britain*. London: Policy Studies Institute

McRae, S (1993) 'Returning to work after childbirth: Opportunities and inequalities'. *European Sociological Review*, Vol 9, 125–138

Macran, S, H Joshi and S Dex (1996) 'Employment after childbearing: a survival analysis'. *Work, Employment and Society* Vol 10, 273–296

Machin, S (1996) 'Changes in the relative demand for skills in the UK labour market' *Acquiring Skills* A Booth and D Snower. Cambridge: Cambridge University Press

Meghir, C and E Whitehouse (1996) 'The Evaluation of Wages in the United Kingdom: Evidence from Micro Data'. *Journal of Labour Economics*, Vol 14, No 1, 1–25

Miller, P (1987) 'The wage effect of the occupational segregation of women in Britain'. *Economic Journal*, Vol 97, 885–896

Oaxaca, R (1973) 'Male-Female Wage Differentials in Urban Labor Markets'. *International Economic Review*, Vol14, No3, 693–709

Oaxaca, R and M Ransom (1994) 'Discrimination and the decomposition of wage differentials'. *Journal of Econometrics*, Vol61, 5–22

Paci, P, H Joshi and G Makepeace (1995) 'Pay Gaps Facing Men and Women Born in 1958: Differences Within the Labour Market' *The Economics of Equal Opportunities* J Humphries and J Rubery. Manchester: Equal Opportunities Commission, 87–111

Paci, P and H Joshi (1996) *Wage differentials between men and women*. Department for Education and Employment Research Series No 71

Payne, J (1990) *Adult Off-the-Job Skills Training*. Employment Department Research and Development Paper No 57

Payne, J, B Casey, C Payne and S Connolly (1996) *Long-term risk factors in unemployment*. London: Policy Studies Institute

Siebert, W and P Sloane (1981) 'The Measurement of Sex and Marital Status Discrimination at the Workplace'. *Economica*, No 48, 125–141

Waldfogel, J (1995) 'The price of motherhood: family status and women's pay in a young British cohort'. *Oxford Economic Papers*, Vol 47, 584–610

Wilkinson, F (1991) 'The structuring of economic and social deprivation and the working of the labour markets in industrial countries'. *Labour and Society*, Vol 16, No 2, 119–138

Wilkinson, F (1992) *Why Britain needs a Minimum Wage*. London: Institute for Public Policy Research

Wright R and J Ermisch (1991) 'Gender Discrimination in the British Labour Market: A Reassessment'. *Economic Journal*, Vol101, No 406, 508–522

Zabalza, A and J Arrufat (1985) 'The extent of sex discrimination in Great Britain' *Women and Equal Pay* A Zabalza and Z Tzannatos. London: Cambridge University Press, 70–96

Appendix

Table 1: *Male–female wage determination models – BHPS Wave One*

	Male equation		*Female equation*	
Variable	*Coefficient*	*t-Stat*	*Coefficient*	*t-Stat*
Constant	1.1899	18.510****	1.1660	24.233****
Personal characteristics				
AGE2534	0.3493	9.036****	0.3002	8.460****
AGE3544	0.4215	8.280****	0.4064	8.333****
AGE4554	0.5087	8.819****	0.4217	6.885****
AGE5564	0.5431	7.334****	0.4372	5.337****
Highest qualification				
CSE	0.0984	2.146**	0.1218	2.771***
OLEVEL	0.2327	7.903****	0.1747	6.895****
ALEVEL	0.3434	10.726****	0.3256	9.650****
HNDHNC	0.5237	12.231****	0.6101	13.890****
DEGREE	0.7020	17.336****	0.6615	16.855****
Work history				
FTEXPER	0.0249	5.353****	0.0274	6.500****
FTXPERSQ	–0.0005	–5.058****	–0.0007	–6.202****
PTEXPER	–0.0772	–3.549****	–0.0179	–3.417****
PTXPRSQ	0.0048	4.002****	0.0005	2.690***
TIMEOUT	–0.0177	–0.925	–0.0212	–4.206****
TIMESQ	0.0005	0.679	0.0005	2.090
Region				
SCOTLAND	–0.2673	–5.887****	–0.2399	–5.993****
WALES	–0.3023	–5.707****	–0.2377	–4.702****
NORTH	–0.2500	–5.218****	–0.2726	–6.082****
NORTHWEST	–0.2159	–5.051****	–0.2187	–5.600****
YORKHUMB	–0.2239	–5.048****	–0.3102	–7.675****
EASTMIDS	–0.3008	–6.610****	–0.3158	–7.296****
WESTMIDS	–0.2405	–5.492****	–0.2877	–6.966****
EASTANG	–0.1704	–2.903***	–0.4108	–7.346****
SOUTWEST	–0.1875	–4.266****	–0.2568	–6.100****
SOUTEAST	–0.0796	–2.083**	–0.1110	–3.162***
Other				
PARTTIME	–0.1507	–2.616***	–0.0704	–3.115***
LAMBDA	–0.2500	–2.681***	–0.1505	–3.403****
Adjusted R2		0.436		0.391
F		59.05		52.19
N		2026		2155
SE		0.431		0.421
Mean LNGHR		1.771		1.457

Notes: Omitted categories are no qualifications, living in London, aged under 25 and working full-time
* = significant at 10%; ** = significant at 5%; *** = significant at 1%; **** = significant at 0.1%

Table 2: *Male–female wage determination models – BHPS Wave Two*

	Male equation		Female equation	
Variable	*Coefficient*	*t-Stat*	*Coefficient*	*t-Stat*
Constant	1.1490	17.158****	1.2054	24.420****
Personal characteristics				
AGE2534	0.2303	5.746****	0.2660	7.136****
AGE3544	0.1932	3.183***	0.3705	6.701****
AGE4554	0.2040	2.793***	0.4326	5.944****
AGE5564	0.3190	5.516****	0.3932	3.995****
Highest qualification				
CSE	0.1042	2.278**	0.0565	1.267
OLEVEL	0.2469	8.951****	0.1959	7.625****
ALEVEL	0.3823	13.064****	0.37112	10.792****
HNDHNC	0.5324	12.631****	0.6125	14.164****
DEGREE	0.8184	21.979****	0.7560	19.064****
Work history				
FTEXPER	0.0416	6.866****	0.0265	5.802****
FTXPERSQ	–0.0007	–6.183****	–0.0006	–5.460****
PTEXPER	–0.0598	–2.960***	–0.0130	–2.384**
PTXPRSQ	0.0042	4.060****	0.0004	2.301**
TIMEOUT	–0.0306	–1.594	–0.0275	–5.303****
TIMESQ	0.0014	1.707*	0.0007	3.288***
Region				
SCOTLAND	–0.2510	–5.794****	–0.2534	–6.356****
WALES	–0.3129	–6.069****	–0.2600	–5.104****
NORTH	–0.2276	–4.970****	–0.2603	–5.728****
NORTHWEST	–0.2331	–5.650****	–0.2670	–6.832****
YORKHUMB	–0.2312	–5.396****	–0.2662	–6.631****
EASTMIDS	–0.3045	–7.045****	–0.3055	–7.046****
WESTMIDS	–0.2259	–5.204****	–0.2704	–6.582****
EASTANG	–0.1553	–2.707***	–0.3027	–5.332****
SOUTWEST	–0.1532	–3.630****	–0.2890	–6.747****
SOUTEAST	–0.0677	–1.855*	–0.1414	–4.102****
Other				
PARTTIME	0.0772	1.235	–0.0467	–1.970**
LAMBDA	–0.1382	–1.526	–0.0911	–2.065**
Adjusted R2		0.426		0.389
F		58.42		52.51
N		2086		2181
SE		0.422		0.427
Mean LNGHR		1.835		1.543

Notes: Omitted categories are no qualifications, living in London, aged under 25 and working full-time

* = significant at 10%; ** = significant at 5%; *** = significant at 1%; **** = significant at 0.1%

Table 3: *Male–female wage determination models – BHPS Wave Three*

	Male equation		*Female equation*	
Variable	*Coefficient*	*t-Stat*	*Coefficient*	*t-Stat*
Constant	1.0606	16.374****	1.2693	23.106****
Personal characteristics				
AGE2534	0.2930	6.575****	0.3078	7.540****
AGE3544	0.2412	3.805****	0.3583	6.091****
AGE4554	0.2690	3.488****	0.3762	4.873****
AGE5564	0.2761	2.888***	0.3920	3.762****
Highest qualification				
CSE	0.1121	2.263**	0.0726	1.575
OLEVEL	0.2484	8.086****	0.1961	7.230****
ALEVEL	0.3772	11.602****	0.3336	9.209****
HNDHNC	0.5574	12.443****	0.6450	13.937****
DEGREE	0.8107	20.996****	0.7452	18.103****
Work history				
FTEXPER	0.0409	6.862****	0.0190	3.899****
FTXPERSQ	–0.0007	–5.665****	–0.0005	–3.653****
PTEXPER	–0.0555	–2.226**	–0.0114	–1.988**
PTXPRSQ	0.0050	2.679***	0.0003	1.514
TIMEOUT	–0.0592	–2.576**	–0.0173	–3.091***
TIMESQ	0.0026	2.597***	0.0007	2.736***
Region				
SCOTLAND	–0.1800	–3.930****	–0.2286	–5.301****
WALES	–0.2181	–3.843****	–0.2786	–5.043****
NORTH	–0.1388	–2.802***	–0.3207	–6.532****
NORTHWEST	–0.1821	–4.078****	–0.2333	–5.540****
YORKHUMB	–0.1540	–3.359****	–0.2372	–5.483****
EASTMIDS	–0.2183	–4.643****	–0.3289	–7.144****
WESTMIDS	–0.2445	–5.322****	–0.2613	–5.581****
EASTANG	–0.1142	–1.846*	–0.3018	–5.110****
SOUTWEST	–0.1382	–3.043***	–0.2424	–5.300****
SOUTEAST	–0.0320	–0.815	–0.1748	–4.762****
Other				
PARTTIME	–0.0544	–0.814	–0.0973	–3.961****
LAMBDA	–0.0548	–0.551	–0.1335	–2.734***
Adjusted R2		0.427		0.391
F		49.38		46.45
N		1753		1910
SE		0.419		0.421
Mean LNGHR		1.861		1.576

Notes: Omitted categories are no qualifications, living in London, aged under 25 and working full-time

* = significant at 10%; ** = significant at 5%; *** = significant at 1%; **** = significant at 0.1%

Table 4: *Male–female wage determination models – BHPS Wave Four*

Variable	*Male equation* Coefficient	*Male equation* t-Stat	*Female equation* Coefficient	*Female equation* t-Stat
Constant	1.1213	14.218****	1.1789	18.838****
Personal characteristics				
AGE2534	0.2739	5.273****	0.2772	5.741****
AGE3544	0.2780	3.827****	0.3854	5.696****
AGE4554	0.2852	3.200***	0.3696	4.160****
AGE5564	0.2699	2.454**	0.3172	2.702***
Highest qualification				
CSE	0.1391	2.475**	0.1618	3.172***
OLEVEL	0.2635	7.520***	0.2397	7.818****
ALEVEL	0.3961	10.795****	0.3597	8.841****
HNDHNC	0.6053	11.883****	0.6517	12.314****
DEGREE	0.8330	18.582****	0.7709	16.901****
Work history				
FTEXPER	0.0357	5.246****	0.0249	4.493****
FTXPERSQ	–0.0006	–4.394****	–0.0005	–3.289***
PTEXPER	–0.0868	–3.573****	–0.0139	–2.118**
PTXPRSQ	0.0062	3.583****	0.0005	2.433**
TIMEOUT	–0.1025	–3.928****	–0.0246	–3.767****
TIMESQ	0.0038	3.371****	0.0009	2.785***
Region				
SCOTLAND	–0.1936	–3.670****	–0.1951	–4.082****
WALES	–0.1603	–2.462**	–0.2936	–4.728****
NORTH	–0.1688	–2.983***	–0.2939	–5.317****
NORTHWEST	–0.1499	–2.944***	–0.2079	–4.336****
YORKHUMB	–0.1812	–3.418****	–0.2399	–4.911****
EASTMIDS	–0.2733	–5.174****	–0.2800	–5.454****
WESTMIDS	–0.2429	–4.685****	–0.2580	–5.080****
EASTANG	–0.1002	–1.505	–0.2614	–4.001****
SOUTWEST	–0.1937	–3.769****	–0.2788	–5.408****
SOUTEAST	–0.0791	–1.785*	–0.1819	–4.403****
Other				
PARTTIME	–0.0619	–0.783	–0.0935	–3.353****
LAMBDA	0.1212	1.019	–0.0048	–0.085
Adjusted R2		0.398		0.358
F		39.83		37.31
N		1586		1761
SE		0.444		0.456
Mean LNGHR		1.904		1.611

Notes: Omitted categories are no qualifications, living in London, aged under 25 and working full-time

* = significant at 10%; ** = significant at 5%; *** = significant at 1%; **** = significant at 0.1%

Table 5: *Male–female wage determination models – EiB*

	Male equation		*Female equation*	
Variable	*Coefficient*	*t-Stat*	*Coefficient*	*t-Stat*
Constant	1.4285	20.147****	1.3510	22.638****
Personal characteristics				
AGE3039	0.0715	1.921*	0.0808	2.238**
AGE4049	0.1116	1.994**	0.0540	1.021
AGE5060	0.1534	2.012**	0.0276	0.376
Highest qualification				
CSE	0.0634	1.385	0.1403	3.024***
OLEVEL	0.1892	6.521****	0.1968	7.221****
ALEVEL	0.3629	9.938****	0.3279	8.909****
HNDHNC	0.4507	11.273****	0.5493	11.726****
DEGREE	0.6732	15.653****	0.6269	14.615****
Work history				
FTEXPER	0.0313	5.033****	0.0270	5.502****
FTXPERSQ	–0.0006	–4.734****	–0.0004	–3.382****
PTEXPER	–0.0208	–1.095	–0.0132	–2.069**
PTXPRSQ	0.0007	0.789	0.0008	2.840***
TIMEOUT	–0.0797	–2.391**	–0.0180	–3.046***
TIMESQ	0.0084	2.975***	0.0007	2.593***
Region				
SCOTLAND	–0.1881	–4.021****	–0.2378	–5.099****
WALES	–0.1982	–3.953****	–0.1960	–3.706****
NORTH	–0.0760	–1.320	–0.2421	–4.150****
NORTHWEST	–0.1284	–3.139***	–0.2041	–4.880****
YORKHUMB	–0.1705	–3.659****	–0.1857	–4.017****
EASTMIDS	–0.1418	–3.166***	–0.1314	–2.692***
WESTMIDS	–0.1604	–3.716****	–0.2159	–4.567****
EASTANG	0.0329	0.480	–0.1060	–1.590
SOUTWEST	–0.1426	–3.054***	–0.1780	–3.823****
SOUTEAST	–0.0275	–0.706	–0.0744	–1.948*
Other				
PARTTIME	–0.0650	–1.030	–0.0459	–1.874*
LAMBDA	–0.0986	–1.117	–0.0083	–0.211
Adjusted R2		0.407		0.361
F		33.20		27.19
N		1221		1208
SE		0.341		0.345
Mean LNGHR		1.863		1.598

Notes: Omitted categories are no qualifications, living in London, aged under 30 and working full-time
* = significant at 10%; ** = significant at 5%; *** = significant at 1%; **** = significant at 0.1%

Table 6: *Female full-time/female part-time wage determination models – BHPS Wave One*

	Full-time equation		*Part-time equation*	
Variable	*Coefficient*	*t-Stat*	*Coefficient*	*t-Stat*
Constant	1.2013	20.351****	1.0727	8.600****
Personal characteristics				
AGE2534	0.2713	6.386****	0.3540	4.776****
AGE3544	0.3959	6.307****	0.4470	4.943****
AGE4554	0.4515	5.713****	0.4306	4.056****
AGE5564	0.4146	3.794****	0.5560	4.181****
Highest qualification				
CSE	0.0648	1.122	0.1945	2.834***
OLEVEL	0.1724	4.970****	0.1554	4.111****
ALEVEL	0.3195	7.448****	0.3004	5.240****
HNDHNC	0.5484	10.322****	0.7419	8.921****
DEGREE	0.6916	14.253****	0.4538	6.088****
Work history				
FTEXPER	0.0309	5.339****	0.0190	2.925***
FTXPERSQ	–0.0008	–5.378****	–0.0005	–2.678***
PTEXPER	–0.0219	–3.004***	–0.0168	–1.599
PTXPRSQ	0.0007	2.126**	0.0005	1.278
TIMEOUT	–0.0201	–2.529**	–0.0179	–2.494**
TIMESQ	0.0004	0.962	0.0003	1.091
Region				
SCOTLAND	–0.2687	–5.411****	–0.1660	–2.432**
WALES	–0.2359	–3.948****	–0.2609	–2.717***
NORTH	–0.2596	–4.608****	–0.2564	–3.466****
NORTHWEST	–0.2760	–5.661****	–0.1031	–1.570
YORKHUMB	–0.3686	–7.298****	–0.2000	–2.961***
EASTMIDS	–0.3213	–5.931****	–0.2699	–3.732****
WESTMIDS	–0.2795	–5.438****	–0.2849	–4.106****
EASTANG	–0.4499	–6.566****	–0.2811	–2.884***
SOUTWEST	–0.2674	–4.849****	–0.2116	–3.093***
SOUTEAST	–0.1160	–2.665***	–0.0716	–1.208
Other				
LAMBDA	–0.1724	–3.780****	–0.1472	–2.001**
Adjusted R2		0.414		0.277
F		37.86		12.72
N		1360		795
SE		0.423		0.410
Mean LNGHR		1.546		1.306

Notes: Omitted categories are no qualifications, living in London, aged under 25 and working full-time

* = significant at 10%; ** = significant at 5%; *** = significant at 1%; **** = significant at 0.1%

Table 7: *Female full-time/female part-time wage determination models – BHPS Wave Two*

Variable	*Full-time equation* Coefficient	t-Stat	*Part-time equation* Coefficient	t-Stat
Constant	1.1444	20.394****	1.3381	8.299****
Personal characteristics				
AGE2534	0.1801	4.370****	0.3746	3.523****
AGE3544	0.2848	4.299****	0.4625	3.558****
AGE4554	0.3033	3.490****	0.6179	4.015****
AGE5564	0.1977	1.652*	0.6948	3.645****
Highest qualification				
CSE	0.0314	0.580	0.0714	0.898
OLEVEL	0.1964	6.065****	0.1824	4.214****
ALEVEL	0.3751	9.221****	0.3732	5.726****
HNDHNC	0.5898	12.301****	0.6852	7.051****
DEGREE	0.8206	17.847****	0.5890	7.158****
Work history				
FTEXPER	0.0405	6.809****	0.0090	1.189
FTXPERSQ	–0.0009	–6.101****	–0.0003	–1.677*
PTEXPER	–0.0072	–1.080	–0.0311	–2.510**
PTXPRSQ	0.0004	1.416	0.0008	1.979**
TIMEOUT	–0.0246	–3.239***	–0.0254	–3.026***
TIMESQ	0.0004	1.121	0.0006	1.861*
Region				
SCOTLAND	–0.2782	–6.202****	–0.2241	–2.818***
WALES	–0.2591	–4.691****	–0.2384	–2.118**
NORTH	–0.2383	–4.586****	–0.2874	–3.258***
NORTHWEST	–0.2584	–5.821****	–0.2955	–3.854****
YORKHUMB	–0.2856	–6.209****	–0.2524	–3.245***
EASTMIDS	–0.2782	–5.704****	–0.3436	–3.965****
WESTMIDS	–0.2615	–5.551****	–0.3089	–3.885****
EASTANG	–0.2961	–4.344****	–0.3219	–3.138***
SOUTWEST	–0.2405	–4.826****	–0.3724	–4.603****
SOUTEAST	–0.1145	–2.972***	–0.1889	–2.718***
Other				
LAMBDA	–0.0572	–1.386	–0.1620	–1.916*
Adjusted R2		0.447		0.236
F		44.41		10.28
N		1398		783
SE		0.394		0.476
Mean LNGHR		1.622		1.400

Notes: Omitted categories are no qualifications, living in London, aged under 25 and working full-time

* = significant at 10%; ** = significant at 5%; *** = significant at 1%; **** = significant at 0.1%

Table 8: *Female full-time/female part-time wage determination models – BHPS Wave Three*

	Full-time equation		Part-time equation	
Variable	*Coefficient*	*t-Stat*	*Coefficient*	*t-Stat*
Constant	1.2114	18.729****	1.1349	8.570****
Personal characteristics				
AGE2534	0.2404	5.088****	0.3504	4.054****
AGE3544	0.2658	3.682****	0.4261	3.898****
AGE4554	0.2953	3.167***	0.4372	3.170***
AGE5564	0.2685	2.085**	0.5737	3.241***
Highest qualification				
CSE	0.0743	1.265	0.0564	0.789
OLEVEL	0.2075	5.872****	0.1832	4.459****
ALEVEL	0.3496	7.911****	0.3173	5.098****
HNDHNC	0.5939	11.077****	0.7947	8.965****
DEGREE	0.7972	16.192****	0.6549	8.638****
Work history				
FTEXPER	0.0311	4.668****	0.0109	1.448
FTXPERSQ	–0.0007	–4.097****	–0.0004	–2.046**
PTEXPER	–0.0159	–2.271**	0.0073	0.612
PTXPRSQ	0.0005	1.707*	–0.0004	–1.198
TIMEOUT	–0.0131	–1.551	–0.0199	–2.438**
TIMESQ	0.0003	0.636	0.0005	1.635
Region				
SCOTLAND	–0.2463	–4.929****	–0.2022	–2.558**
WALES	–0.2417	–3.853****	–0.3734	–3.564****
NORTH	–0.2355	–4.007****	–0.4411	–5.176****
NORTHWEST	–0.1956	–3.943****	–0.3086	–4.085****
YORKHUMB	–0.2788	–5.438****	–0.2093	–2.732***
EASTMIDS	–0.2983	–5.394****	–0.3657	–4.558****
WESTMIDS	–0.2171	–4.033****	–0.3383	–4.348****
EASTANG	–0.3403	–4.555****	–0.2709	–2.846***
SOUTWEST	–0.1988	–3.622****	–0.3141	–3.968****
SOUTEAST	–0.1341	–3.173***	–0.2556	–3.756****
Other				
LAMBDA	–0.1170	–2.402**	–0.0046	–0.062
Adjusted R2		0.420		0.256
F		34.13		10.49
N		1191		719
SE		0.403		0.425
Mean LNGHR		1.681		1.403

Notes: Omitted categories are no qualifications, living in London, aged under 25 and working full-time
* = significant at 10%; ** = significant at 5%; *** = significant at 1%; **** = significant at 0.1%

Table 9: *Female full-time/female part-time wage determination models – BHPS Wave Four*

	Full-time equation		Part-time equation	
Variable	*Coefficient*	*t-Stat*	*Coefficient*	*t-Stat*
Constant	1.1461	15.528****	1.1781	7.148****
Personal characteristics				
AGE2534	0.2633	4.638****	0.2172	1.981**
AGE3544	0.3568	4.234****	0.3802	2.909***
AGE4554	0.3211	2.898***	0.3986	2.477**
AGE5564	0.1763	1.179	0.4741	2.394**
Highest qualification				
CSE	0.1903	2.757***	0.1382	1.828*
OLEVEL	0.2564	6.148****	0.2040	4.511****
ALEVEL	0.3764	7.334****	0.3576	5.276****
HNDHNC	0.6653	10.599****	0.6464	6.375****
DEGREE	0.8357	15.104****	0.5743	6.673****
Work history				
FTEXPER	0.0331	4.302****	0.0069	0.776
FTXPERSQ	–0.0006	–3.258***	–0.00002	–0.076
PTEXPER	–0.0191	–2.421**	–0.0094	–0.641
PTXPRSQ	0.0006	1.923*	0.0002	0.436
TIMEOUT	–0.0169	–1.790*	–0.0273	–2.842***
TIMESQ	0.0003	0.658	0.0010	2.302**
Region				
SCOTLAND	–0.2773	–4.820****	–0.0317	–0.374
WALES	–0.2814	–3.706****	–0.2682	–2.508**
NORTH	–0.3095	–4.429****	–0.2113	–2.317**
NORTHWEST	–0.2363	–4.029****	–0.1311	–1.590
YORKHUMB	–0.2979	–4.962****	–0.1094	–1.311
EASTMIDS	–0.3008	–4.792****	–0.1841	–2.093**
WESTMIDS	–0.2858	–4.577****	–0.1621	–1.862*
EASTANG	–0.2747	–3.284***	–0.1881	–1.792*
SOUTWEST	–0.3001	–4.510****	–0.2035	–2.445**
SOUTEAST	–0.1809	–3.646****	–0.1314	–1.795*
Other				
LAMBDA	–0.0024	–0.043	–0.0630	–0.703
Adjusted R2		0.385		0.187
F		27.25		6.89
N		1093		668
SE		0.449		0.453
Mean LNGHR		1.723		1.428

Notes: Omitted categories are no qualifications, living in London, aged under 25 and working full-time
* = significant at 10%; ** = significant at 5%; *** = significant at 1%; **** = significant at 0.1%

Table 10: *Female full-time/female part-time wage determination models – EiB*

	Full-time equation		*Part-time equation*	
Variable	*Coefficient*	*t-Stat*	*Coefficient*	*t-Stat*
Constant	1.2767	17.024****	1.3339	9.715****
Personal characteristics				
AGE3039	0.0468	1.031	0.0868	1.400
AGE4049	0.0494	0.729	0.0256	0.766
AGE5060	0.0362	0.375	0.0246	0.217
Highest qualification				
CSE	0.1530	2.518**	0.1165	0.604
OLEVEL	0.1925	5.220****	0.2100	5.136****
ALEVEL	0.3507	7.655****	0.2724	4.226****
HNDHNC	0.5439	9.279****	0.5911	7.522****
DEGREE	0.6238	11.820****	0.6892	8.669****
Work history				
FTEXPER	0.0384	5.666****	0.0166	2.115**
FTXPERSQ	–0.0007	–4.181****	–0.0003	–1.057
PTEXPER	–0.0181	–2.290**	0.00004	0.003
PTXPRSQ	0.0011	2.774***	0.0002	0.467
TIMEOUT	–0.0244	–3.004***	–0.0124	–1.403
TIMESQ	0.0011	2.748***	0.0004	0.948
Region				
SCOTLAND	–0.2467	–4.524****	–0.2291	–2.575**
WALES	–0.1870	–2.838***	–0.2380	–2.558**
NORTH	–0.2544	–3.482****	–0.2708	–2.710***
NORTHWEST	–0.1999	–4.042****	–0.2243	–2.790***
YORKHUMB	–0.1592	–2.742***	–0.2293	–2.786***
EASTMIDS	–0.0709	–1.230	–0.2658	–2.925***
WESTMIDS	–0.2208	–3.844****	–0.2453	–2.869***
EASTANG	–0.1479	–1.720*	–0.0890	0.804
SOUTWEST	–0.1608	–2.672***	–0.2097	–2.554**
SOUTEAST	–0.0097	–0.219	–0.2005	–2.656***
Other				
LAMBDA	–0.0291	–0.673	0.0528	0.831
Adjusted R2		0.373		0.251
F		18.07		7.52
N		720		488
SE		0.337		0.347
Mean LNGHR		1.687		1.465

Notes: Omitted categories are no qualifications, living in London, and aged under 25
* = significant at 10%; ** = significant at 5%; *** = significant at 1%; **** = significant at 0.1%

Table 11: *Variable definitions*

Variable	*Definition*
Personal characteristics	
AGE2534	Dummy=1 if age 25–34
AGE3544	Dummy=1 if age 35–44
AGE4554	Dummy=1 if age 45–54
AGE5564	Dummy=1 if age 55–64
AGE3039	Dummy=1 if age 30–39
AGE4049	Dummy=1 if age 40–49
AGE5060	Dummy–1 if age 50–60
Highest qualification	
CSE	Dummy=1 if highest qualification is CSE equivalent
OLEVEL	Dummy=1 if highest qualification is 'O' Level equivalent
ALEVEL	Dummy=1 if highest qualification is 'A' Level equivalent
HNDHNC	Dummy=1 if highest qualification is between 'A' Level and degree
DEGREE	Dummy=1 if highest qualification is degree
Work History	
FTEXPER	Year of full-time work experience
FTXOERSQ	Years of full-time work experience squared
PTEXPER	Years of part-time work experience
PTXPERSQ	Years of part-time work experience squared
TIMEOUT	Years in non-employment
TIMESQ	Years in non-employment squared
Region	
SCOTLAND	Dummy=1 if living in Scotland
WALES	Dummy=1 if living in Wales
NORTH	Dummy=1 if living in the North
NORTHWEST	Dummy=1 if living in the North-west
YORKHUMB	Dummy=1 if living in Yorkshire and Humberside
EASTMIDS	Dummy=1 if living in the East Midlands
WESTMIDS	Dummy=1 if living in the West Midlands
EASTANG	Dummy=1 if living in East Anglia
SOUTWEST	Dummy=1 if living in the South-west
SOUTEAST	Dummy=1 if living in the South-east
Other	
PARTIME	Dummy=1 if working part-time
LAMBDA	Variable correcting for sample selection bias
Dependent variable	
LNGHR	Natural logarithm of the gross hourly rate