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**The Gender Gap in Early-Career Wage Growth**

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## **Abstract**

In the UK the gender pay gap on entry to the labour market is approximately zero but after ten years after labour market entry, there is a gender wage gap of almost 25 log points. This paper explores the reason for this gender gap in early-career wage growth, considering three main hypotheses - human capital, job-shopping and 'psychological' theories. Human capital factors can explain about 12 log points, job-shopping about 1.5 log points and the psychological theories about half a log point. But a substantial unexplained gap remains: women who have continuous full-time employment, have had no children and express no desire to have them earn about 12 log points less than equivalent men after 10 years in the labour market.

Keywords: Gender Pay Gap, Wage Growth

JEL Classifications: J24, J31, J7

Data: BHPS, BCS, NES, LFS

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## Introduction

This paper is about the gender pay gap in the UK. Given the enormous literature on the gender pay gap (see Altonji and Blank, 1999, for a relatively recent survey) one might wonder about the justification for yet another paper on the subject. The answer is that this paper focuses on the gender gap in wage growth in the early years after labour market entry and argues that an understanding of this is necessary as it is the primary cause of the overall gender pay gap. The reason why this is particularly important in the UK can be explained very simply.

Figure 1 presents the data the earnings-experience profile in the UK for men and women together with the gender pay gap from one of the main data sets used in this paper, the British Household Panel Survey (BHPS). Average log wages are normalized to be zero for men with zero years of labour market experience. One can see that the earnings of men and women are very similar on entry to the labour market but 10 years later a sizeable gender gap in earnings has emerged, a gap that reaches its maximum about 20 years after labour market entry before falling slightly in later years<sup>1</sup>. Of course, cross-section profiles like the ones presented in Figure 1 confound true life-cycle effects and cohort effects. But, while cohort effects can probably explain some of the cross-section profile, there is good reason to think that they are not the most important reason for the widening of the gender pay gap after labour market entry. To see this Figure 2 presents the gender earnings gap at different ages for different birth cohorts in the New Earnings Survey (NES)<sup>2</sup>. The NES contains no information on education (so we cannot compute experience) and Figure 2 simply presents age profiles. What one can see is that the gender pay gap is lower at all ages for younger cohorts but that the contribution of cohort is small relative to the life-

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<sup>1</sup> This convergence in later years is less apparent in the BHPS than in other British data sets like the Labour Force Survey.

<sup>2</sup> The BHPS is too short a panel to follow cohorts through time.

cycle effects. For example, Figure 2 suggests that the gender pay gap that can be expected at age 40 for those born around 1970 is likely to be smaller than for those born around 1960 but extrapolation of the profiles in Figure 2 would suggest that a very sizeable gender wage gap will still exist. And for women born after 1970 there is some evidence that the progress of women has stalled as the profiles of the gender pay gap are very similar for those born around 1970 and those born in the late 1970s – if this is true then there will be a gender pay gap for these women of 20 log points in their early 30s<sup>3</sup>. So, young women entering the labour market today can still expect to earn much less than young men after 10 years in the labour market and this gender difference in early-career wage growth needs explaining.

Most papers on the gender pay gap focus on the level of pay and not the growth in pay. But as the level of pay at any level experience is simply the initial pay on labour market entry plus cumulated wage growth any theory of the pay level must be, if only implicitly, also a theory of wage growth (and vice versa). So, theories to explain the level of pay should also be able to explain differences in wage growth. This paper focuses on three theories of wage growth – the human capital hypothesis, job-shopping and ‘psychological’ theories and asks how well they can do in explaining the gender gap in early-career wage growth.

The most common approach to explaining the gender pay gap is based on the human capital model developed by Becker (1993) and Mincer (1974) and applied to the gender pay gap in many papers (e.g. see Mincer and Polachek, 1974, Mincer and Ofek, 1982, Light and Ureta, 1995 inter alia). This approach seeks to explain the gender pay gap by gender differences in human capital accumulation of which there are several dimensions. First, there are gender differences in accumulated work

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<sup>3</sup> The flattening in the gender pay gap that one sees in the early 20s in Figure 2 is the result of the entry at that age into the labour market of college graduates for whom, on labour market entry, the gender pay gap is small.

experience (which is assumed to be correlated with levels of human capital) because women are more likely to have intermittent labour market participation and are more likely to work part-time. Secondly, the anticipation of future intermittence may affect current investments in human capital. The affected investments might be after labour market entry (see Ben-Porath, 1967, for a classic theoretical model of this) or prior to labour market entry where it may take the form of gender differences in the quantity or (more plausible these days for a country like the UK) type of education. Thirdly, Becker (1985) has argued that the greater domestic commitments of women (especially married women with dependent children) means they put less energy into work and that translates into lower hourly wages.

The estimates presented below find that the human capital hypothesis can explain some of the gender gap in early-career wage growth but most of the gender pay gap that emerges by 10 years after labour market entry cannot be explained in this way. The reason for this conclusion can be explained very simply. First, differences in actual labour market experience between young British men and women after 10 years in the labour market are simply not large enough to explain more than 6.5 of the 25 log-point gender pay gap at that point in the life-cycle. Secondly, gender differences in job-related training do explain a part of the differential (primarily because young men are still much more likely than young women to go into apprenticeships) but, again, the estimated contribution is no more than 4.5 log points. And, thirdly, gender differences in the quantity of education are very small (and, in any case, Mincer's (1974) famous observation that the experience profiles are similar for different levels of education would suggest that any difference in the quantity of education should show up in a gender pay gap on labour market entry and not a gender gap in wage growth), and, while gender differences in the types of education

and associated occupational choices are still large, we do not find that occupational differences contribute much to the gender gap in early-career wage growth. The bottom line is that the human capital explanations can explain perhaps half of the 25 log point gender pay gap observed 10 years after labour market entry.

The paper then also investigates the job-shopping hypothesis that an important part of early career wage growth is associated with moving from worse to better-paying jobs (e.g. Topel and Ward, 1992 who study only US men find that something like one-third of wage growth in the first 10 years after labour market entry can be put down to job mobility). Manning (2003a, ch7) has documented how women are more constrained in their opportunities to change jobs than men and are less concerned with money when they do. So we might expect to see women making fewer ‘good’ job changes, more ‘bad’ job changes and a lower return to job changes when they do. We investigate this hypothesis below, and find that it can explain only 1.5 log points of the gender pay gap after 10 years in the labour market. This is not because job mobility is unimportant but because gender differences in job mobility among young workers are quite small.

The paper then considers a more recent but less well-known theory of the gender pay gap – that has its roots in psychological differences in the behaviour of men and women that they bring with them to the labour market. In their book, ‘Women Don’t Ask: Negotiation and the Gender Divide’, Babcock and Laschever (2003) argue that a powerful cause of women’s disadvantage is that they tend to have a lower opinion of themselves than men so do not ask their bosses for what they want and passively accept wage offers rather than bargain for better conditions. We use data on psychological attributes of men and women before labour market entry to test this hypothesis. We find that there are returns to ‘personality’ (as has been found by

others – see Goldsmith et al, 1997, Feinstein, 2000, Bowles et al, 2001) but the gender differences and the returns are not large enough to explain more than roughly half a log point of the gender pay gap that emerges after 10 years in the labour market.

The plan of the paper is as follows. The next section describes the data used in the paper. The second section then presents ‘reduced-form’ estimates of wage growth equations that confirm the presence of a gender gap in early-career wage growth as suggested by Figure 1. The third section then investigates the extent to which this can be explained by differences in human capital considering the contribution of breaks in employment, of job-related training, of the types of education and of occupational choice. The fourth section then considers the contribution of job mobility, both good and bad, to wage growth. The fifth section then investigates the importance of ‘personality’ for explaining the gender pay gap. The bottom line is that a considerable part of the gender pay gap after 10 years in the labour market remains unexplained: a woman who has done nothing but work full-time ever since leaving education, has had no children and expresses no desire to have them in the future earns, on average, at least 10 percentage points less than an equivalent man. The conclusion makes some suggestions about possible directions for further research.

## 1. The Data

The main data used in the first part of this paper comes from the first 12 waves of the British Household Panel Study (BHPS) that cover the period 1991-2002 inclusive though the Labour Force Survey (LFS) the New Earnings Survey (NES) are sometimes used for supplementary evidence and consistency checks. The BHPS started in 1991 with some 5500 households and 10,300 individuals drawn from 250 different areas of Great Britain. It has had a number of booster samples:

approximately 1000 households in 1997 that are part of the European Community Household Panel Survey (that include Northern Ireland and over-sample low-income households), approximately 3000 Scottish and Welsh households that were added in 1999. It follows all individuals in sample households and those who end up in households with them as long as they remain in a household with an original sample member (in many ways, it can be thought of as the British PSID).

From the BHPS the sample is constructed in the following way. First, the sample is restricted attention to those with no more than 10 years of potential labour market experience as our focus is on what happens to the gender pay gap in the years after labor market entry. Secondly, only those individuals for whom there is an uninterrupted set of interviews are included. Thirdly, anyone who has a period in employment when we cannot identify whether they are working for the same employer as at the previous interview is excluded. Finally, because of the difficulty in measuring earnings for the self-employed anyone who reported being self-employed at any interview date is excluded: as few individuals move between employment and self-employment (about 1.5% of employees become self-employed in any year) this is a relatively minor restriction. In total about 5% of observations are excluded because of data problems and the final sample used for analysis is approximately 10500 observations on wage growth for about 3559 individuals.

Wages are measured as an hourly rate, obtained by dividing usual weekly earnings by usual weekly hours. Those with hourly earnings below £1 or above £100 are excluded. As we do not want the measure of earnings growth on-the-job to include aggregate wage growth it is important to deflate wages: as Altonji and Williams (1998) point out, estimates of the return to job tenure can be sensitive to the

way in which this is done<sup>4</sup>. We experimented with the use of an external earnings index but average earnings growth in the BHPS deviates from this aggregate measure. As a result we estimated a simple earnings function of the log of hourly wages on a quartic in experience, regional, race and gender dummies and a set of wave dummies and then deducted the wave dummies to generate our adjusted wage series.

As we are interested in how wages evolve, we need a measure of wage growth. In most studies of wage growth, the dependent variable is defined as the growth in wages between two fixed points in time, with this measure being undefined for those who are not in employment at either of the two points. This approach has the disadvantage that it under-samples those individuals who have intermittent employment, a potentially serious problem when analyzing the gender pay gap. For example, suppose we measure wages annually but some individuals have a year or more in which they are not in employment. If one only measures wage growth from one year to the next, one will drop two observations for such individuals because there will be two years in which annual wage growth is not defined. To deal with this problem, we define wage growth in the following way. For any year in which an individual is in employment, define the wage growth as the difference in log wages between the next year they are in employment and the log wage this year.

Consequently there may be gaps between the two wage observations of any number of years. It is important to control for this ‘gap’ in what follows and we describe later how we do this. There remains a potential problem in that the gap between wage observations is censored at the top end by the latest year of observation being 2002

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<sup>4</sup> This is less important in the current context where we are primarily interested in the gender gap in wage growth than in the literature on the returns to job tenure as incorrect detrending probably has a very similar effect on both men and women.

but this seems to be a small problem<sup>5</sup> because long gaps between wage observations are relatively rare. The first two columns of Table 1 presents the distribution of gaps between the wage observations in our data set for men and women. One observes, as one would expect, that women are more likely than men to have intermittent employment. But, what is also striking is the relatively short length of gaps between periods of employment (see also Myck and Paull. 2001, for an analysis of gender differences in accumulated experience). Only 2% of the observations on female wage growth have a gap in employment of more than 2 years. Because the BHPS is a relatively short panel, there are many censored observations so, to get some idea of the uncensored distribution of the gap the third and fourth columns of Table 1 report the distribution of the gap among those in waves 1-6. There are now more young women with longer gaps in employment though it remains remarkable how rare are long breaks in employment. However this data is still censored: some women may never return to paid employment but some might have very long spells that are not observed in the BHPS. To get some idea of this, the final two columns of Table 1 presents, for comparison, data on gaps between spells of employment from the LFS. In the LFS those not currently in employment are asked when they last worked and we can use this information to work out the gap between employment spells for those who are employed in the subsequent quarter<sup>6</sup>. Again, one sees that women are more likely to have gaps in employment than men but the average size of gaps and the gender differences are not large – the BHPS suggests an average gap for women that is 0.3 years above that for men and the LFS suggests a somewhat smaller gap of 0.25 years. And the very long gaps that contribute quite a lot to this overall gender

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<sup>5</sup> We did experiment with restricting the sample to those in the early waves when censoring is less problematic: this made no difference to the conclusions.

<sup>6</sup> Note that in a steady-state it should not matter whether one looks forward as in the BHPS or backwards as in the LFS.

difference are very rare among the young workers that are the focus of this paper. For example, the work history data of the 1970 British Cohort Study suggests that, among those in employment at age 30, 23% of men have had a period of non-employment between two periods of employment with an average of 0.3 gaps compared to 27% of women with an average of 0.35 gaps.

One other peculiarity of the BHPS that is worth mentioning is that its basic measure of job tenure is tenure in a particular job with a particular employer so that within-firm changes of job reset the tenure clock to zero. This is not the way that the job tenure variable is usually defined where it refers to job tenure with the same employer. However, the BHPS definition is retained here as job moves within employers (e.g. promotions) are as interesting and important as those between employers in understanding the emergence of the gender pay gap<sup>7</sup>. The data is summarized in the Appendix in Table A1.

## 2. Reduced Form Estimates

While the evidence presented in Figures 1 and 2 is strongly suggestive of a gender gap in wage growth in the years immediately after labour market entry, it is important to verify this using direct data on wage growth. Hence, this section presents some ‘reduced-form’ wage growth regressions to get some idea of what the data looks like and to confirm the existence of this gender gap in early-career wage growth.

Accordingly, we estimate the following ‘reduced-form’ model for the wage growth between  $t$  and  $(t+g)$  of individual  $i$  where  $g$  is the gap between wage observations:

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<sup>7</sup> Furthermore, attempting to construct more traditional measures of job tenure results in a large fall in the number of useable observations because the work history information needed to construct it is only available for a fraction of the sample.

$$\Delta w_{it} = \beta_0 + \beta_1 e_{it} + \beta_2 e_{it}^2 + \varepsilon_{it} = \phi(e_{it}) + \varepsilon_{it} \quad (1)$$

where  $e$  is years since leaving full-time education i.e. potential experience. This model is estimated separately for men and women. The quadratic specification seems adequate to capture the variation in wage growth among the young workers in our sample but one should be wary of extrapolating into other parts of the life-cycle (Murphy and Welch, 1990, suggest a quartic for the level implying a cubic for the change if workers of all ages are in the sample).

In specifying this equation we need to be careful about how we deal with individuals for whom the gap over which wage growth is measured is more than a year. To see why this matters suppose that the observed wage growth for all individuals (whatever the gap) was 5% but that men are always in employment (so  $g=1$ ) but women are only in employment every two years (so  $g=2$ ). After 2 years earnings for men would have grown by approximately 10% whereas those for women would have only grown by 5%. The gender pay gap would be widening but estimation of (1) that did not take account of differences in the gap would miss this.

The simplest way of getting a gap-adjusted measure of wage growth would be to simply divide the observed wage growth by the gap between wage observations to get an estimate of annualized wage growth. However the validity of this procedure is based on the implicit assumption that wage growth does not vary with experience, something we know to be untrue. So, a slightly more sophisticated approach is taken here to adjust for the gap between wage observations. If (1) is the wage growth for those for whom  $g=1$ , then for someone with  $g=2$  to return to employment at the same level of wages they must have expected wage growth between the two observations of:

$$E(\Delta w_{it}) = \phi(e_{it}) + \phi(e_{it} + 1) \quad (2)$$

the right-hand side of which is simply two one-period sets of wage growth. One can readily extend this formula to any value of  $g$  in which case it will be given by:

$$E(\Delta w_{it}) = \sum_{j=0}^{g-1} \phi(e_{it} + j) \quad (3)$$

Using the specific functional form in (1), this can be written as:

$$E(\Delta w_{it}) = \beta_0 g + \beta_1 \sum_{j=0}^{g-1} (e_{it} + j) + \beta_2 \sum_{j=0}^{g-1} (e_{it} + j)^2 \quad (4)$$

Thus one can readily estimate wage growth on a consistent basis for individuals with different gaps by computing the ‘adjusted’ levels of experience in (4) and using these as regressors in a wage growth equation. Note that there is no constant in this regression - the constant in (1) gets multiplied by  $g$ . If wage growth does not vary with experience this approach is equivalent to the simple-minded approach of just dividing wage growth by the interval between wage observations as the gap would be the only remaining regressor and the coefficient on it can be interpreted as annual wage growth.

Table 2 reports estimates of the reduced-form wage growth equations. The first two columns of Table 2 report estimates of (4) for men and women separately. We report the estimates of earnings growth at 0, 5 and 10 years of experience together with their standard errors. Taking the coefficients for men, the estimates suggest that a man can expect 14.5% annual wage growth on entry into the labour market, falling to 6.8% after 5 years and 1.3% after 10 years. For women (the second column) earnings growth on entry is lower than for men (at 12.0% per annum) and still lower after 10 years though the gap in wage growth narrows<sup>8</sup>. These estimates are consistent with the finding that the gender pay gap begins to widen soon after labour market entry, as

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<sup>8</sup> One might wonder whether these gender differences are significantly different from each other. At each individual level of experience the answer is often ‘no’ but one can easily reject the joint hypothesis that the returns to experience for men and women are equal in the first 10 years.

suggested in Figure 1<sup>9</sup>. The bottom two rows of Table 2 report the gender pay gap implied by these differences in estimated wage growth 5 and 10 years after labour market entry. These are derived by cumulating the estimates of the gender difference in wage growth from the estimation of (4) assuming that there are no breaks in employment and (as is a good approximation) that gender differences in wages on labour market entry are zero. The estimates in columns 1 and 2 of Table 2 imply a gender pay gap of 14.4 log points after 5 years and 24.8 log points after 10 years. These estimates are not far out of line with those derived from estimates of wage levels.

To check that these estimates are not sensitive to the treatment of those with gaps of more than 1 year between wage observations, columns 3 and 4 of Table 2 present the ‘reduced-form’ wage growth equations restricting the sample to those for whom the gap between wage observations is only one year. One finds the same pattern of gender differences in wage growth. The implied gender pay gap after 10 years is lower for this sample at 22.2 log points suggesting that part of the overall gap can be explained by women having more intermittence but the contribution is not that large, suggesting that there are not large gender gaps in labour market attachment among young workers.

One might also wonder whether the inclusion of other controls on individual characteristics alter these conclusions. The bottom line is that they do not have a big impact<sup>10</sup>. One way to see the irrelevance of personal characteristics is to estimate

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<sup>9</sup> Note that, averaging across men and women of all experience levels, there is no significant difference in wage growth - as found by Manning and Robinson (2004). However, that paper makes the (embarrassing) mistake of inferring from this fact that gender differences in wage growth cannot explain the gender pay gap. This is wrong because a male advantage in wage growth in early life offset by a female advantage in later life does not imply a zero gender pay gap.

<sup>10</sup> One proviso to this is that there is some evidence that in the reduced form, the earnings growth is lower in the early years for the best-educated. But, this can be explained by the larger amount of on-the-job training received in the early years by the less-educated and this is a variable for which we do control later in the paper.

wage growth equations including individual fixed effects. This is done in the final two columns of Table 2: the coefficients hardly change and the fixed effects are jointly insignificant from zero. We should not be surprised by this finding: if there were very significant permanent differences in wage growth across individuals one would expect to see the variance of earnings in a cohort rising explosively over the life-cycle which it does not<sup>11</sup>. Of course, this insignificance of fixed effects in a wage-growth equation does not mean that individual fixed effects would not be very significant in a wage *levels* equation – rather, it is a validation of Mincer’s conclusion that earnings profiles are parallel to each other (once one controls for gender).

So, our basic data do contain the feature that there is a noticeable gender gap in wage growth from the start of labour market careers. Although this gender gap in wage growth eventually reverses there is a very large gender pay gap by the time it does and women never make up the ground lost in the first 10 years after labour market entry. One might be concerned that this conclusion applies only to the BHPS or is an artifact of the quadratic specification used. So, as a useful double-check, Figure 3 presents data from the NES that has a large enough sample size to get precise estimates of wage growth for men and women at each age. This shows the same pattern as the BHPS. It is this gender gap in early-career wage growth that this paper seeks to explain.

### 3. Gender Differences in Human Capital Accumulation

Human capital theories seek to explain the gender pay gap by gender differences in human capital accumulation. There is no doubt that human capital theory is of use in explaining at least some part of the gender pay gap – some researchers (e.g. O’Neill,

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<sup>11</sup> See Mincer (1974) and, more recently, by Heckman Lochner and Todd (2002) for a discussion of the variance profile.

2003, and Polachek, 2004) claim that it can explain virtually all of the US gender pay gap while others (e.g. Altonji and Blank, 1999, Blau and Kahn, 2004), find that there remains a sizeable unexplained component to the gender pay gap. There are several varieties of human capital explanations for the gender pay gap all of which have their root in “the lesser amount of time and energy that women can commit to labour-market careers as a result of the division of labour within the family” (O’Neill, 2003, p309). First, after labour market entry, the weaker labour market attachment of women means they tend to accumulate less labour market experience than men and, given that such experience is valuable, part of the difference in earnings can be explained as the result of this difference in actual labour market experience. Studies (e.g. see Mincer and Polachek, 1974, or Light and Ureta, 1995) sometimes find that the returns to actual experience is very similar for men and women though typically other measures of labour market history are also important in explaining the gender pay gap and a sizeable part of the gender pay gap remains unexplained even after controlling for differences in actual labour market experience<sup>12</sup>.

Secondly, there may be differences in human capital investments after labour market entry in anticipation of future labour market attachment. So, we might see men doing more job-related training than women because they expect to spend longer in the labour market in later years. Thirdly, a similar argument might apply to human capital investments in education prior to labour market entry – men might make more investments than women in human capital that has a labour market pay-off. We consider these three different human capital hypotheses in turn.

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<sup>12</sup> And one should also note that actual labour market experience is endogenous so that part of the correlation of wages with actual experience may not be causal.

## *Gender Differences in Labour Market Experience*

First, consider whether gender differences in actual labour market experience (the results of more labour market intermittence and more part-time working by women) can explain the gender gap in early-career wage growth.

In our framework labour market intermittence is captured by the gap between wage observations as a gap of more than one year must imply a period not in employment. As shown in Table 1, women have longer gaps between wage observations than men implying that women do have weaker labour market attachment than men. It may be that the differences in the gap variable can explain the disadvantage of young women in wage growth. The specification of the wage-growth equation used so far assumes that there is no wage penalty associated with having  $g > 1$  but there are good reasons to think there might be a penalty. Assume that each year in which one is out of employment reduces the level of wages when one returns by  $\beta_5$  log points<sup>13</sup>. Then the equation for wage growth (4) will become:

$$E(\Delta w_{it}) = \beta_5 + \beta_0 g + \beta_1 \sum_{j=0}^{g-1} (e_{it} + j) + \beta_2 \sum_{j=0}^{g-1} (e_{it} + j)^2 \quad (5)$$

so that a simple way to test for a penalty to intermittent employment is to include constants in the reduced-form wage growth equations. This is done in the first and second columns of Table 3. These results suggest that each year out of employment reduces wages by 4.4% for men and 4.7% for women. The estimate for men is slightly lower but broadly consistent with the penalty for spells of unemployment found by Arulampalam (2001) and Gregory and Jukes (2001).

But the implied gender pay gap after 10 years (for those without any intermittence) only falls from 24.8 to 22 log points suggesting a contribution of

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<sup>13</sup> In some of the literature (notably Mincer and Ofek, 1982), there is a debate about whether it is the incidence or the length of the break in employment that is the more important. But, as Table 2 makes clear we do not really have sufficient variation in the employment gap in our data to explore this further.

intermittence of 2.8 log points (this is similar to the estimate from columns 3 and 4 of Table 2).

Women accumulate less work experience than men, not just because they have more intermittence but also because they are more likely to work part-time. For example, in our sample, 3.6% of the men are working part-time (defined as less than 30 hours a week) and 19.2% of the women. The third and fourth columns of Table 3 include a dummy variable for whether the individual is currently working part-time. The few men who are working part-time have a very large penalty of 19.3 log points while the part-time women have a pay penalty of 6.0%. The implied gender gap after 10 years for those who work continuously full-time now falls to 18.3% suggesting a contribution of the gender difference in part-time working of 3.7%. This is probably an over-estimate as hourly earnings are obtained by dividing weekly earnings by reported hours leading to a division bias problem that overstates the initial wages of those in part-time employment.

The estimates so far suggest that differences in actual work experience when young can explain at most 30% of the gender gap in early-career wage growth. The explanation for this is simple: the gender gap in wage growth is largest when the gender gap in accumulated actual labour market experience is rather small. To further illustrate this Figure 4 presents data from the 1970 British Cohort Study, a longitudinal of all children born in Britain in one week in 1970 and which collects monthly information on labour market status. Figure 4 shows the gender differences in actual experience (measured as months in work) over the first 10 years after labour market entry. 10 years after labour market entry the men have accumulated about 12 months more work experience than the women. The gap in full-time experience is larger at 20 months. However, for the purpose of understanding the gender pay gap

for those in work (as is the focus of this paper) these differences are misleading as the pay differences relate to those in work and the gender differences in actual experience are much smaller for those in work. These differences are also plotted on Figure 4: after 10 years male workers have about 3 months more work experience than women and about 12 months more full-time experience. These differences are simply not large enough to explain the magnitude of the gender pay gap after 10 years: for example, if one thinks of the male profile as being the ‘true’ one and women are one year behind men after 10 years this can only account for wage differentials of the order of 2 log points. The contribution is a bit larger if one recognizes that the earnings profile is concave so it is not just the mean but also the variance that is of importance and women have slightly higher variance than men. After 10 years the gender difference in the variance of full-time work experience among workers is about 1 year which adds at most an extra one log point to the predicted gender difference. These back-of-the-envelope calculations are smaller than the regression estimates of Table 3 though, as we have already noted, the contribution of part-time working is probably over-estimated.

The discussion so far has focused on the accumulation of general human capital but gender differences in the accumulation of specific human capital might also be important. Job-specific human capital is often assumed to be measured by job tenure (see Mincer and Jovanovic, 1981, for this theoretical argument and Jones and Makepeace, 1996, for a British study in which this variable is important for explaining a gender gap). The fifth and sixth columns of Table 3 include job tenure in the current job as an extra control in the wage-growth equations. We find that higher job tenure is associated with significantly lower wage growth. But, this does little to narrow the gender gap in wage growth on labour market entry and has no impact on

the implied gender pay gap after 10 years.

### *Gender Differences in On-the-Job Training*

Of course, it may be differences in expected future labour market attachment that affect current human capital accumulation either before or after labour market entry. Let us start with the training after labour market entry. In the BHPS respondents are asked about the total amount of job-related training they have done over the previous year. We simply include a measure of the total years of training received as a control variable in our wage growth regression. We might expect that current job-related training depresses current wages but raises future wages and wage growth. However, the strongest empirical effect of on-the-job training seems to come not from the measure of the training received between the two wage observations but from the measure of training received over the year prior to the initial wage observation. So, measures of training in both years are included in the wage growth regressions: the results are presented in columns 7 and 8 of Table 3. The return to a year of job-related training for men is higher (at approximately 8-10%) than for women (approximately 3% for training received in the past year and zero for training between wage observations).

The difference in the return to training is compounded by the fact that young men receive more on-the-job training than young women – for example among workers with less than 5 years of potential experience, the men receive on average 0.039 years of training per year and the women 0.032. This seems to be the result of the fact that men (especially those with little education) are much more likely than women to be in apprenticeships (which have a very large training component). Among men who leave school at 16 but are aged 20 or under 25% are in

apprenticeships compared to 10% of women (figures from the 2004 LFS). Figure 5 shows that the gender gap in education is entirely driven by the behaviour of the low-educated: among college-graduates young women receive more training than young men. When one cumulates this one can see that the predicted gender wage gap after 10 years falls to 0.138 from 0.183 when one controls for training so something like 4.5 log points of the gap after 10 years can be explained by gender differences in the receipt and the return to on-the-job training.

### *Gender Differences in Occupation and Education*

Now let us consider gender differences in human capital accumulation before labour market entry. In terms of the quantity of education there are few gender differences (see the summary statistics in Table A1). But the type of education may be different e.g. Brown and Corcoran (1997), Black et al (2003) for the US and Machin and Puhani (2002) for the UK and Germany document that differences in subject of degree can explain a portion of the gender pay gap among college graduates. Unfortunately the BHPS does not contain detailed information on the subjects studied by college graduates or others. But it does contain information on the occupation of the first job that might be expected to capture much of gender differences in career choices.

Columns 9 and 10 of Table 3 include dummy variables for the occupation in the first job so the assumption is that initial choice of occupation has a permanent effect on wage growth<sup>14</sup>. Sample sizes preclude using more than 1-digit occupation controls but there are sizeable gender differences even at this level in the type of job first done. Details are in Table A1 in the data appendix but the big differences

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<sup>14</sup> We did experiment with interacting first job with years of experience so the impact of initial job falls over time but the coefficients on these interactions were always insignificantly different from zero.

among young workers (with less than 10 years of potential experience) are that 38% of women first enter clerical and secretarial occupations compared to 16% of men, 20% of women enter personal and protective service occupations compared to 8% of men, 2% of women enter craft occupations compared to 23% of men and 7% of women enter elementary occupations compared to 15% of men.

In producing the summary statistics on wage growth at different levels of experience and the gender gap we assume a distribution of first jobs equal to the average across men and women with less than 10 years of experience – evaluating at male or female characteristics makes no difference. For both men and women the coefficients on initial occupation are jointly not significantly different from zero though the rejection is marginal for men (the rather curious mix of managerial, professional, clerical and elementary occupations seem to have higher wage growth than the others). But, when it comes to explaining gender differences in wage growth, initial occupation has little explanatory power with the predicted gender pay gap after 10 years falling from 0.138 to 0.124 after controlling for initial occupation<sup>15</sup>.

However this evidence has only used 1-digit controls for initial occupation and one might be concerned that more marked differences would emerge if a finer measure of occupation was used. That is not possible because of small sample sizes in the BHPS but we can get some idea of whether this is likely using the much larger sample sizes available in the NES where we can use 3-digit occupation of which there are approximately 370. Once one goes to this level of disaggregation there is a problem that some occupations are so overwhelmingly dominated by one gender that one has very few observations on the other. To deal with this problem of matching

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<sup>15</sup> One might be concerned that the sample sizes in columns 9 and 10 are considerably smaller than in columns 7 and 8 because initial job is missing for many observations. But, estimating the model of columns 7 and 8 using the restricted sample of columns 9 and 10 leads to a predicted wage gap after 10 years of 0.13 so the contribution of occupation is probably smaller than it appears from a simple inspection of Table 3.

men and women at the 3-digit occupation level the sample is restricted to occupations that have at least 2% of the minority gender. This excludes from the sample 17.5% of men in 74 occupations (broadly, production managers in manufacturing and construction, senior police and fire officers, drivers of trains, boats, and planes, almost all of construction, almost anything that involves metal-working, and refuse collection). 9.6% of women are excluded in 9 occupations (broadly, midwives, secretaries, dental nurses, childcare workers and beauticians).

We take two approaches to controlling for occupation. In the first we simply include a dummy variable for each occupation in the gender-specific wage growth equations effectively assuming that occupation only affects the level and not the life-cycle profile of wage growth. The results are summarized in Panel A of Figure 6. The line marked ‘whole sample’ reproduces the raw gender gap in wage growth already shown in Figure 4. The line ‘matched sample’ reports the raw gap in wage growth for those in occupations that are not excluded from the analysis – one notices that the gender gap in wage growth is now much smaller for those aged 16-22. The most likely explanation for this finding is that many of the men who are excluded from the matched sample are in construction and/or metal-working trades and the young men in particular are doing apprenticeships that is associated with fast wage growth. This is consistent with our earlier finding of gender differences in training receipt among this group.

The remaining two lines in Figure 6A show the impact of adjusting the matched sample for differences in the gender distribution of occupation. We show two estimates – one evaluated at the male occupation distribution and one at the female occupation – though they are very similar and similar to the line that does not control for occupational segregation at all. Figure 6A suggests a sizeable gender pay

gap in early-career wage growth remains even after controlling for differences in occupation.

However, the estimates that lie behind Figure 6A assume an impact of occupation on wage growth that can be modeled as a shifting intercept. This is quite restrictive e.g. it might be the case that women, anticipating future labour market withdrawal, go into occupations that offer high initial wage growth and slower wage growth later on. To allow for this possibility we also present – in Figure 6B – a re-weighting estimator that uses the methodology of diNardo, Fortin and Lemieux (1996) to re-weight the female (resp. male) data to reproduce the male (resp. female) occupational distribution. We then report weighted wage growth by age. The resulting estimates of the gender gap in wage growth are much noisier than the regression-based estimates (unsurprisingly because less structure is put on the data) but one can still see that virtually all of the observations of the gender gap in wage growth up to the age of 35 are positive. So, differences in occupation do not seem to be able to explain much of the gender-gap in early-career wage growth once one has controlled for gender differences in training.

This conclusion that occupational differences cannot explain much of the gender gap in early-career wage growth can be reconciled with the findings of Machin and Puhani (2003) that field of study can explain a sizeable part of the gender wage gap among British college graduates. Firstly, there is a small gender wage gap on entry to the labour market among graduates that can be explained almost entirely by differences in field of study but field of study seems to have little impact on wage growth. Secondly, gender differences in curriculum are larger for graduates than non-graduates (as is found for the US by Brown and Corcoran, 1997).

### *Conclusions on the Human Capital Hypothesis*

The evidence presented here suggests that human capital factors can explain perhaps half of the gender gap in early-career wage growth. Of the overall 25 log point gap implied after 10 years, 2.8 log points can be explained by differences in labour market intermittence, 3.7% by differences in part-time working, 4.5% by differences in training (primarily because young men who leave school early are still more likely to do apprenticeships) and perhaps 1.5% by differences in occupational choice. Labour market intermittence and part-time working is more important between 10 and 20 years after labour market entry for the reason that this is when most women have breaks in employment associated with childcare. The bottom line is that a woman who works continuously full-time can expect to be 12% behind an equivalent man after 10 years in the labour market.

#### 4. Job-Shopping Models

Part of the rapid wage growth in the years immediately after labour market entry may be the result of job mobility – finding a good match for one’s skills or simply finding the good jobs (if, as evidence suggests, there is a sizeable amount of equilibrium wage dispersion). Theoretical analysis of the implications of job search models for the returns to experience and job tenure can be found in Burdett (1978) and Manning (1997, 2000). Topel and Ward (1992) found that for US men something like a third of wage growth in the first 10 years after labour market entry can be ascribed to job mobility.

In this process of job-shopping it seems plausible that there are gender differences. For example Manning (2003a, ch7) documents, using the BHPS, that women are more constrained in their job choices (primarily by family commitments),

they travel less far to work (again, suggesting a narrower choice of jobs – see Manning, 2003b) and their job changes are less motivated by money and are less likely to be ‘for a better job’. All of these factors might be expected to be potential explanations of the gender gap in early-career wage growth.

First, consider gender differences in job mobility. For current purposes we define job mobility rates as the percentage of those currently in employment for whom the next observation is non-employment or a change in job. Note that a change in job need not be associated with a change in employer so a promotion will count as a ‘job’ change (see Booth et al, 2003, for an analysis of promotions in the BHPS). Figure 7 presents the overall job mobility rates by experience for men and women. One sees the well-known pattern that job mobility rates start off very high, then decline before flattening out and rising slightly for the older workers. Women have noticeably higher mobility rates than men between 10 and 25 years of experience i.e. in the prime child-bearing years.

It is likely that there are gender differences in the types of job mobility as well as the level. Although there is an argument (based on a frictionless competitive labour market) that there is no meaningful distinction between quits and lay-offs (see McLaughlin, 1991) most labour economists think there is a useful distinction between quits that are voluntary on the part of workers and lay-offs that are not. Consistent with this, quits tend to be associated with wage gains while lay-offs are associated with wage losses (see, for example, Ruhm, 1991, Jacobson et al, 1993, Kletzer, 1998). The job history files of the BHPS record reasons for why jobs ended and Table 4 tabulates them. 47% of young men leave jobs because they are promoted or get a

better job compared to 43% of women<sup>16</sup>. 15% of male jobs end in redundancy or dismissal compared with only 9% of women. 7% of female jobs end to have a baby or look after other family with, unsurprisingly, this proportion being close to zero for men. To summarize, male jobs are slightly more likely to end with a move to a better job, but men are more at risk of jobs ending because of redundancy. On the other hand, women's jobs are more likely to end to have a child.

Not all job changes have reasons associated with them (approximately 12% do not). But, we can get an idea of the relative importance of different mobility rates for different sorts of job change by multiplying the overall mobility rate by the fraction of job changes due to particular reasons (this implicitly assumes that the job changes with no given reason are drawn at random). To prevent information overload we divide reasons for jobs ending in two categories: those that end with a move to a better job and those that don't. Figure 8 presents the experience profiles for changes to a better job for men and women: there are no large gender differences. Figure 9 presents the job mobility rates not to a better job: this is higher for women in the early years of the labour market, primarily because of the role played by family responsibilities. These figures suggest that over the first 10 years in the labour market men can expect 3 good job moves (compared to 2.9 for women) and 2 bad job moves (compared to 2.4 for women).

Now let us consider the extent to which wage changes are related to different sorts of mobility. There is an existing literature on the impact of different sorts of moves on wage changes that starts with a series of papers in the early 1980s (Bartel, 1980, 1982; Borjas, 1981; Bartel and Borjas, 1981). More recent papers are Topel

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<sup>16</sup> There is also a question about why the new job is better, the reasons for which can be crudely divided into pecuniary and non-pecuniary reasons. We did experiment with disaggregating the 'left for better job' category but there are many missing values and ambiguous answers (e.g. many saying they left for a better job because the new job is better) so this was not pursued.

and Ward (1992) and, with a specific focus on gender differences, Loprest (1992), Crossley et al (1994), Keith and McWilliams (1997, 1999), and Cobb-Clark (2001).

We examine the impact of job mobility by simply including dummy variables for different sorts of move<sup>17</sup>. There are a large number of reasons for moves given in Table 4 and we aggregate these into four categories: moves for a better job (called ‘good moves’), moves because jobs ended in redundancy, dismissal or end of contract (called ‘bad’ moves), moves that end for family reasons (called ‘kid’ moves) and moves for other reasons (called other moves). This is relatively crude: for example Gibbons and Katz (1991) provide evidence that those dismissed suffer a greater wage penalty than those made redundant through plant closure. But, we do not have enough data here to do a very fine disaggregation.

The first two columns of Table 5 provide estimates of wage growth equations augmented by job mobility variables. For men a ‘good’ move is associated with a wage gain of 8.6% while for women it only produces a gain of 6.3%. This result that the returns to job mobility are lower for women is consistent with the evidence presented in Manning (2003, ch7). ‘Bad’ moves are associated with significant wage losses- 3.9% for men but not for women. For kid moves, there is a very large pay penalty for the small number of men who make such a move but the most interesting finding is that there is no wage penalty associated with such moves for women (the coefficient is actually positive though insignificantly different from zero). This is different from the findings in Waldfogel (1998) or Joshi and Paci (1998) but those use data from a much earlier period and find that the wage penalty is smaller for women with maternity leave entitlements who return to the same employer. As these

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<sup>17</sup> There are reasons to doubt whether this specification is adequate. For example, theory predicts some variation in the returns to job mobility both in observables (like experience, job tenure and the current level of wages) and unobservables (because individuals are less likely to leave jobs with high wage growth). However, experimentation with the specification did not lead to any substantive change in the results and we only report the simplest specification here.

entitlements have been extended it is possible that now there is a relatively small penalty associated with having children if the woman returns to paid work quickly (there is a penalty to intermittence of employment as captured by the gap variable). Finally the ‘other’ move category has insignificant effects on wage growth.

The inclusion of the job mobility variables essentially leaves the implied gender pay after 10 years of continuous employment slightly higher than it was without the job mobility variables (compare columns 1 and 2 of Table 5 with columns 7 and 8 of Table 3). But, the specification used here assumes that there is no heterogeneity in the returns to job mobility. In particular, the theory of job-shopping would suggest that very young workers will not suffer much of a wage loss when making a bad move because they have little to lose but older workers will face larger wage losses because they are more likely to have worked themselves into a good job<sup>18</sup>. To test this hypothesis we also included an interaction of experience with a bad move – the results are reported in columns 3 and 4 of Table 5. For both men and women this interaction variable is negative though the coefficient is much larger for men (probably because older men have more to lose than older women). As predicted by the theory, the coefficient on the bad move variable itself is insignificantly different from zero (this is the estimate of the cost of a bad move for a worker just entering the labour market). Accordingly the fifth and sixth columns of Table 5 include only the interaction of bad moves with experience. The implied gender pay gap after 10 years for those who remain in the same job now falls to 0.122 suggesting a contribution of job mobility of 1.5 percentage points (comparing with columns 7 and 8 of Table 3). This modest contribution is not because job mobility has no effect on wage growth, just that the differences between young men and women are not that

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<sup>18</sup> The theory might also be used to predict other interactions but, while we experimented with other interactions, we never found any to be significant.

large. Hence, job-shopping models do not appear to be able to explain more than a small part of the gender gap in early-career wage growth.

#### 5. Personality and the Gender Pay Gap

In recent years a number of studies have demonstrated intriguing correlations between earnings and ‘personality’ variables<sup>19</sup> (e.g. Goldsmith and Darity, 1997, Feinstein, 2000, Bowles, Gintis and Osbourne, 2001, and Nyhus and Pons, 2004). A natural extension of this work is to investigate the hypothesis that psychological differences between men and women on entry into the labour market can explain part of the gender pay gap. This hypothesis has been investigated directly using Dutch data by Mueller and Plug (2004) but is also related to the experimental work on behavioural differences between men and women in competitive environments (see, for example, Gneezy and Rustichini, 2002, and Gneezy, Niederle and Rustichini, 2003). The most explicit statement of the idea that gender differences in personality can help to explain the labour market disadvantage of women is the book, ‘Women Don’t Ask: Negotiation and the Gender Divide’ - Babcock and Laschever (2003). They argue that a powerful cause of women’s disadvantage is that they do not ask their bosses for what they want, because they do not think change is possible or because they do not attach as high a value to their labour as do men or because they fear damaging a relationship or because society reacts badly to assertive women. Among many other anecdotes, they give the example of MBAs graduating from Carnegie-Mellon. The men earned 7.6% more on average than the women but this difference arose solely because most women accepted the initial offer with only 7% negotiating whereas for

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<sup>19</sup> This research can be seen as one part of the renaissance in behavioural economics that seeks insights from psychology for application in economics.

men the figure was 57%<sup>20</sup>.

It seems fairly obvious that these differences in personality have the potential to explain not just gender differences in the level of wages but also gender differences in early-career wage growth analyzed in this paper. For example, women may be less ‘pushy’ than men so do not get ahead so fast. In this section we use data on childhood personality to investigate this hypothesis in a more quantitative way than was done by Babcock and Laschever<sup>21</sup>. We find that, while there are some psychological differences between men and women and there are returns to ‘personality’ (as has been found by the other studies cited above) the differences and the returns are not large enough to explain much more than roughly half a log point of the gender gap that emerges after 10 years in the labour market.

The BHPS has collected data on youths living within sample households since wave 4 and asks them, among other things, the questions described in Table 6. The answers to these questions show that a higher incidence of lower self-image and greater self-doubt in young women as compared to young men. For example, when asked to agree or otherwise to the statement “I don’t have much to be proud of” 13.9% of male youths agreed compared to 17.5% of females. The lower self-image for females is shown even more starkly as the responses to the statements “I certainly feel useless at times” showed 29.1% of male youths agreeing compared to 44.8% of females. In addition, 22.6% of male youths compared to 35.3% of females agreed with the statement “At times I feel I am no good at all”. These differences might be expected to produce wage differentials in later life if the Babcock-Laschever

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<sup>20</sup> This finding is reminiscent of the evidence (albeit for a rather old cohort) presented by Wood, Corcoran and Courant (1993) who found a large unexplained wage gap of the order of 20% among lawyers even after controlling for a very detailed set of labour market attitudes.

<sup>21</sup> Some studies use personality information collected at the same time as the individual's earnings raising obvious potential endogeneity problems. We hope that the use of childhood personality variables avoids these difficulties.

hypothesis is correct. Unfortunately the BHPS panel is not long enough to provide a large enough sample of previously surveyed youths who are then observed earning in the labour market so that we cannot, as yet, use the BHPS for this purpose.

For this reason we turn to another data set, the British Cohort Study (BCS) that also contains the type of data required to investigate the impact of personality on the gender wage gap. The BCS is a cohort of all individuals born in a single week in 1970 (see Joshi and Paci, 1998, for more description of this data). Information has been collected on the cohort at a variety of ages: here we use the latest information collected in 2000, for 30 year old individuals which have been (roughly) 10 years in the labour market. In addition we use the detailed information collected before they entered the labour market - during their childhood and adolescence - on their personality. These personality controls are constructed using the cohort members' questionnaire responses at age 10 and 16.

The two personality variables that we use are the Lawseq "self-esteem" and the Caroloc "locus of control" scores that are based on the child's responses to a series of questions. We have two measures, one based on age 10 responses and the other on age 16 responses. The higher the reported score, the higher is the individual's self-esteem and locus of control is assessed to be. The self-esteem measure is essentially a measure of how much an individual values themselves and the locus of control score is an indicator of the individual's degree of inner-directedness or how much the individual feels their actions can affect what happens to them in life.<sup>22</sup>

Although the primary aim of this section is to investigate the impact of the personality variables on the gender wage gap, it is important to establish that our earlier findings about the gender pay gap in the BHPS are also found in the BCS. As

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<sup>22</sup> See Osborn and Milbank (1987) for a discussion of how the self-esteem and locus of control scores are constructed.

the BCS only has information on earnings at a few points in time we focus on the gender pay gap in 2000 when the cohort members were aged 30 and had, on average, been in the labour market for approximately 10 years. But, we are estimating the level of the gender pay gap (which can be thought of as cumulated wage growth) rather than direct estimates of the gender gap in wage growth

Table 7 presents some estimates of the gender pay gap using the BCS 2000, We start with the estimation of equations similar to those we have used for the BHPS. The structure of the table is as follows: in the second column we present the raw gender pay gap for the sample under consideration. The third column then reports the coefficient on a dummy variable for being male when other controls are introduced. The third (resp. fourth) column then reports the results when separate earnings equations for men and women are estimated and the gender pay gap evaluated for a full-time worker with 10 years of actual experience whose other characteristics match those of the average woman (resp. man)<sup>23</sup>.

The raw gender pay gap is approximately 18 log points for the wage levels as shown in the second column of the first row, somewhat lower than estimates from the BHPS<sup>24</sup>. When controls for whether there are children in the household, marital status, race, tenure and qualifications are introduced (but not fertility intentions or actual labour market experience) the estimated gender wage gap falls to approximately 16 log points (row 1, column 3). The second row adds in the expected future fertility controls – a dummy for whether the individual is planning (further) children in the future but the impact of this control is negligible.

In the third row a quadratic for total labour market experience is included.

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<sup>23</sup> Our reason for showing this particular gender gap is that this is closest to the cumulated gap that has been the focus of attention in the BHPS data.

<sup>24</sup> It is worth noting that throughout this section we use wage levels rather than wage growth because that is the only data available to us. But, as the gender gap is approximately zero on labour market entry this should not make a huge difference.

This has a relatively small impact on the wage gap estimates, reducing slightly the wage gap with controls and the wage gap evaluated with male characteristics. In comparison, the inclusion of full-time and part-time actual labour market experience in the row below (row 4) has a much greater impact on the wage gap estimates. The estimated gender wage gap with controls (column 3) reduces by roughly 4 log points. The unexplained pay gap also falls by roughly 4 log points. The fourth row includes one-digit occupation controls – the unexplained gender gap rises when evaluated for the average man by almost 3 log points. The figures based on the female evaluated wage gaps are similar to the wage gap estimates (with controls) in the previous (third) column. All of these estimates suggest a pay gap in the region of 11-16% between British men and women aged 30 in 2000 who have spent all their careers in full-time employment, an estimate similar to that derived from the BHPS earlier in the paper.

To illustrate this even more starkly, the fifth row restricts the sample to those individuals who at age 30 have not had any children and who have had every month in full-time employment since leaving full-time education. These are individuals whose commitment to the labour force cannot be questioned. The raw gender pay gap for this group is 8.1 log points but the adjusted gender pay gaps are larger at 11%, primarily because women in this group are better educated than the men. It should be noted that there is no correction for sample selection bias here - such a correction is likely to make the adjusted gender pay gap even bigger as the ‘career’ women are likely to be much more positively selected than the ‘career’ men. The final row shows that the inclusion of 1-digit occupation makes little difference to the conclusion for this group. These estimates are also in line with the unexplained gender pay gap reported in Dolton, Joshi and Makepeace (2002). Having established that the BHPS and BCS data lead to similar conclusions, we turn to the impact of personality

variables.

Table 8 presents the gender differences in the self-esteem and locus of control variables in the BCS. There is no significant gender difference at either age 10 or 16 in the locus-of-control measure and the only significant difference in the self-esteem measure is at age 10 where the men have greater self-esteem than the women. Thus, in the BCS data, the differences in personality are rather small.

Table 9 presents evidence on the returns to self-esteem and locus-of-control from separate male and female wage equations (the equation includes a full-set of controls as described previously). In row 1 the age 10 self-esteem and locus of control scores are included in the age 30 wage equations and the comparisons of the estimates highlights some interesting gender differences. For example, the impact of the self-esteem control in the female wage equation is positive, significant and more than three times the magnitude of the male (insignificant) estimate when the control is from age 10. In comparison neither the male or female estimate of the impact of the age 16 self-esteem control (row 2) is significant, whereas the female coefficient estimate in row 3 is again significant and positive for the sample restricted to those who responded to BCS at age 10 and 16.

Also shown in table 9 are the estimates for the impact of the locus of control scores on the wage. In row 1 the coefficient estimates for the scores collected at age 10 are positive and significant for both male and female employees. The magnitudes are similar but the male estimate is ever so slightly larger. Using the age 16 locus of control score, the male and female estimates are both positive. However, only the female estimate is significant and it is roughly twice the magnitude of the male estimate. Restricting the sample to those that responded to the age 10 and 16 BCS survey results in both estimates becoming significant (row 3).

The consequences of the differences in personality variables presented in Table 8 and the returns to those variables presented in Table 9 for the gender pay gap are summarized in Table 10. In the first row the gender wage gap estimates based on the basic wage equation are presented for a sample of individuals at age 30 who also responded to the BCS age 10 survey. Compared to Table 7 this restriction reduces the sample size by roughly 1,000 observations for both male and female employees but the raw log wage differential remains almost identical to that of the full sample. The second row shows the gender wage gap when controls for self-esteem and the locus of control are included. These two controls have a relatively small impact on the wage gap, reducing the wage gap with controls and the wage gaps evaluated at the male and female characteristics with 10 years of experience by roughly half a log point. In rows 3 and 4 the gender wage gaps are presented for those individuals at age 30 who also responded to the age 16 BCS survey. These results also suggest a relatively small or negligible impact of the self-esteem and locus of control scores on the gender wage gap. In rows 5 and 6 the gender wage gaps are presented for those individuals at age 30 who also responded to both the age 10 and 16 BCS survey. The estimated impact of the personality controls are slightly larger here – reducing the wage gaps evaluated at the male characteristics by roughly 2 log points and at the female characteristics by slightly more than half a log point.<sup>25</sup>

It seems fair to conclude that the power of the personality hypothesis, evaluated using the self-esteem and locus of control scores, to reduce the unexplained portion of the gender wage gap is very limited. The reason is that, although there are returns to ‘personality’, these returns are not large enough and the differences between the sexes not big enough for these variables to be capable of explaining more than 1-2

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<sup>25</sup> The sample sizes are much reduced in rows 3-6 due to the teacher strike in 1986, which affected the BCS 1970 age 16 follow-up survey response rate.

log points of the gender pay gap at age 30. Of course, it is possible that we have not measured the right personality variables to test the Babcock and Laschever (2003) hypothesis<sup>26</sup> but the self-esteem and locus-of-control variables do seem close to the ideas expressed in that book about women having a relatively low opinion of their own abilities and being fatalistic about the ability to change things for themselves.

## 6. Conclusions

This paper has argued that an understanding of the gender pay gap in Britain needs to focus on the explanation of the gender gap in early-career wage growth that causes women who entered the labour market with the same average level of pay as men to be approximately 25 log points behind 10 years later. Human capital theory can explain at most half of this (primarily because of gender differences in the receipt of on-the-job training, and because of modest differences in accumulated labour market experience). Job shopping theories seem to be able to explain at most 1.5 log points and the ‘psychological’ hypothesis of Babcock and Laschever (2003) seems to explain little more than half a log point. There remains a large unexplained component. This gender gap in wage growth means that, although men and women have similar earnings when entering the labour market, the women will be something like 12% behind the men ten years later even if they have been in continuous full-time employment, have had no children and do not want any.

What theories might be of use in explaining this large residual component to the gender gap in early-career wage growth? A simple ‘discrimination’ view does not seem very helpful as the gender pay gap is zero on labour market entry though it is

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<sup>26</sup> We did experiment with including attitudes collected during adolescence about the relative importance of future job characteristics and expectations about their future educational activities. These variables had slightly more explanatory power than the direct personality variables but still could not explain more than 1-2 percentage points of the gender pay gap at age 30.

perhaps now more difficult to exercise prejudice on entry to jobs. But, there some other possibilities.

First, differences in the ambitions of men and women could be important. A number of papers (e.g. Vella, 1994, Swaffield, 2000, Chevalier, 2004) find that differences in ambitions about how important is career (relative to family, for example) and what one seeks in a job (e.g. money versus helping people) can help to 'explain' the gender pay gap. However these papers tend to use information on ambitions approximately contemporaneous with that on wages so reverse causality may be a problem.

A second possibility is that theories of statistical discrimination might have some explanatory power. We have sought to explain the wage growth of individual women using their individual experiences and plans but some of this (e.g. future fertility plans) might be private information that is hard for employers to know in which case all women will be judged on the basis of 'averages'. Lazear and Rosen (1990) construct one such theory in which the greater likelihood of women quitting induces employers to make less investment in them and to promote them less often (see Pekkarinen and Vartianen, 2004, for an application of these ideas to Finnish metalworkers). One could argue that this particular mechanism is controlled for here once we introduce on-the-job training and promotions but one could construct other theories of statistical discrimination that would account for gender differences in wage growth within jobs.

Whether these or other explanations can explain the residual 12 point wage gap faced by career women after 10 years in the labour market is something we leave for future research.

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**Table 1**  
**Distribution of Gap between Successive Wage Observations**

Gap between wage obs (yrs)	BHPS (all waves)		BHPS (wave<=6)		LFS	
	Men	Women	Men	Women	Men	Women
1	95.6	93.0	94.7	91.5	96.6	92.7
2	3.1	4.8	3.3	5.2	2.4	3.1
3	0.9	0.9	1.1	1.1	0.4	1.1
4	0.2	0.4	0.4	0.8	0.2	0.6
5	0.1	0.2	0.1	0.4	0.1	0.5
6	0.1	0.3	0.1	0.5	0.1	0.4
7	0.0	0.1	0.0	0.3	0.0	0.3
8	0.7	0.1	0.2	0.2	0.0	0.3
9	0.0	0.0	0.0	0.0	0.0	0.2
10-14					0.1	0.7
15-19	0.0	0.0	0.0	0.1	0.0	0.1
20+					0.0	0.0
No. of obs	5344	5756	2709	2990	37384	34595

Notes.

1. BHPS sample is restricted to those with 10 or fewer years of potential labour market experience.
2. LFS sample is from 1997-2002 and gives the distribution among those currently in employment who are not labour market entrants and who have less than 20 years of labour market experience.

**Table 2**  
**'Reduced Form' Estimates of Wage Growth Equation**

	1	2	3	4	5	6
	Men	Women	Men	Women	Men	Women
0 yrs of experience	0.145 (0.013)	0.120 (0.012)	0.161 (0.013)	0.131 (0.011)	0.160 (0.019)	0.160 (0.016)
5 yrs of experience	0.068 (0.005)	0.040 (0.004)	0.070 (0.004)	0.046 (0.004)	0.074 (0.008)	0.041 (0.006)
10 yrs of experience	0.013 (0.010)	0.009 (0.006)	0.030 (0.007)	0.035 (0.007)	0.018 (0.015)	0.020 (0.011)
No. of obs	5015	5535	4833	5208	5015	5535
R <sup>2</sup>	0.076	0.051	0.077	0.058	0.020	0.015
Fixed Effects	No	No	No	No	Yes	Yes
Sample	All	All	Gap=1	Gap=1	P=1.00 All	P=1.00 All
Implied Gender Gap at 5 yrs	0.144 (0.044)		0.149 (0.041)		0.096 (0.062)	
Implied Gender Gap at 10 yrs	0.248 (0.054)		0.222 (0.044)		0.216 (0.066)	

Notes.

1. These estimates are derived from the estimation of (4) where experience is modeled as a quadratic.
2. Standard errors in parentheses. These are robust standard errors with clustering on the individual.

**Table 3**  
**The Impact of Human Capital Variables on the Gender Gap in Wage Growth**

	1	2	3	4	5	6	7	8	9	10
	Men	Women	Men	Women	Men	Women	Men	Women	Men	Women
0 yrs of experience	0.151 (0.013)	0.130 (0.011)	0.172 (0.013)	0.141 (0.011)	0.173 (0.013)	0.141 (0.011)	0.153 (0.013)	0.138 (0.011)	0.118 (0.021)	0.088 (0.013)
5 yrs of experience	0.074 (0.005)	0.046 (0.004)	0.077 (0.005)	0.056 (0.004)	0.063 (0.008)	0.043 (0.006)	0.059 (0.008)	0.040 (0.007)	0.049 (0.010)	0.026 (0.004)
10 yrs of experience	0.023 (0.009)	0.032 (0.008)	0.028 (0.009)	0.046 (0.008)	-0.003 (0.014)	0.014 (0.012)	-0.004 (0.014)	0.010 (0.012)	-0.001 (0.019)	0.025 (0.004)
Cost of gap>1	0.044 (0.024)	0.047 (0.015)	0.046 (0.024)	0.059 (0.015)	0.054 (0.024)	0.066 (0.016)	0.054 (0.025)	0.067 (0.017)	0.119 (0.029)	0.093 (0.021)
Part-Time			-0.193 (0.041)	-0.060 (0.011)	-0.194 (0.041)	-0.062 (0.012)	-0.189 (0.042)	-0.060 (0.012)	-0.153 (0.045)	-0.066 (0.014)
Decades of job tenure					-0.040 (0.017)	-0.041 (0.015)	-0.037 (0.017)	-0.045 (0.015)	-0.044 (0.023)	-0.068 (0.021)
Training in Past Year (yrs)							0.087 (0.058)	0.028 (0.038)	0.119 (0.091)	0.073 (0.031)
Training between wage obs (yrs)							0.107 (0.063)	-0.005 (0.035)	0.077 (0.081)	-0.039 (0.046)
No. of obs	5015	5535	5015	5535	5015	5535	4830	5306	2505	3127
R <sup>2</sup>	0.078	0.055	0.090	0.061	0.091	0.062	0.088	0.060	0.064	0.042
Controls for Initial Occupation	No	No	No	No	No	No	No	No	Yes P=0.07	Yes P=0.14
Implied Gender Gap at 5 yrs	0.136 (0.042)		0.147 (0.042)		0.146 (0.046)		0.096 (0.049)		0.062 (0.095)	
Implied Gender Gap at 10 yrs	0.220 (0.045)		0.183 (0.048)		0.183 (0.086)		0.138 (0.091)		0.124 (0.165)	

Notes.

1. These estimates are derived from the estimation of (5) where experience is modeled as a quadratic and, where appropriate, a dummy variable for having intermittent employment, a part-time dummy, years of job tenure and years of training and is included.
2. Standard errors in parentheses. These are robust standard errors with clustering on the individual.
3. In columns 5 to 10 the estimates of the gender gap after 5 and 10 years are based on assuming no change in job so job tenure rises with experience. In columns 7 to 10 the estimates of the gender gap after 5 and 10 years are based on assuming no receipt of on-the-job training. Full-time work is always assumed.
4. In columns 9 and 10 where initial occupation is included as a control, the estimates of wage growth and the gender gap are based on the average using the distribution of initial occupation across both men and women with less than 10 years of experience. Using the male or the female distribution makes no difference to the results. The p-value for a test of the hypothesis that occupational variables are jointly insignificant from zero is also reported.

**Table 4**  
**Reasons Given for Jobs Ending**

Reason given	Men (%)	Women (%)
Promoted	19.1	16.7
Left For Better Job	28.0	26.9
Made Redundant	12.7	7.8
Dismissed or Sacked	3.1	1.4
Temporary Job Ended	10.5	9.8
Took retirement	1.9	2.9
Health Reasons	3.6	4.2
To Have Baby	0.0	3.7
Children/Home care	0.5	3.9
Moved Area	3.6	5.0
Other	17.1	17.1
No. of obs	3611	3749

Notes.

1. Sample is restricted to BHPS from waves 5 on as extra categories then added. Refers to those with between 0 and 10 years of labour market experience inclusive. Data refer to reasons given for job ending.

**Table 5**  
**The Impact of Job Mobility on Wage Growth**

	Men	Women	Men	Women	Men	Women
0 yrs of experience	0.135	0.120	0.130	0.112	0.131	0.107
	(0.014)	(0.012)	(0.014)	(0.012)	(0.014)	(0.012)
5 yrs of experience	0.051	0.029	0.047	0.028	0.047	0.022
	(0.008)	(0.007)	(0.008)	(0.006)	(0.008)	(0.006)
10 yrs of experience	-0.005	0.013	-0.001	0.013	-0.001	0.005
	(0.015)	(0.012)	(0.014)	(0.012)	(0.014)	(0.012)
Cost of gap>1	0.031	0.041	-0.002	0.033	-0.001	0.036
	(0.037)	(0.017)	(0.037)	(0.019)	(0.036)	(0.019)
Part-Time	-0.193	-0.060	-0.194	-0.061	-0.194	-0.060
	(0.043)	(0.012)	(0.043)	(0.012)	(0.043)	(0.012)
Decades of tenure	-0.017	-0.031	-0.022	-0.032	-0.023	-0.033
	(0.018)	(0.015)	(0.018)	(0.015)	(0.018)	(0.015)
Training in Past Year (yrs)	0.082	0.011	0.081	0.011	0.080	0.011
	(0.058)	(0.038)	(0.059)	(0.038)	(0.059)	(0.038)
Training between wage obs (yrs)	0.085	-0.001	0.088	-0.002	0.087	-0.003
	(0.066)	(0.035)	(0.066)	(0.035)	(0.065)	(0.035)
Good Move	0.086	0.063	0.087	0.063	0.087	0.063
	(0.011)	(0.010)	(0.011)	(0.010)	(0.011)	(0.010)
Bad Move	-0.039	0.013	0.008	0.029		
	(0.022)	(0.023)	(0.031)	(0.027)		
Bad Move* Decades of experience			-0.890	-0.277	-0.813	-0.143
			(0.452)	(0.240)	(0.323)	(0.202)
Kid Move	-0.143	0.041	-0.189	0.033	-0.186	0.035
	(0.176)	(0.052)	(0.182)	(0.053)	(0.181)	(0.053)
Other Move	-0.032	0.006	-0.037	0.004	-0.037	0.005
	(0.021)	(0.019)	(0.021)	(0.019)	(0.021)	(0.019)
No. of Obs	4762	5142	4762	5142	4762	5142
R <sup>2</sup>	0.105	0.072	0.106	0.073	0.106	0.073
Gender Gap at 5 yrs		0.108		0.087		0.081
		(0.052)		(0.052)		(0.052)
Gender Gap at 10 yrs		0.155		0.127		0.122
		(0.090)		(0.091)		(0.091)

Notes.

1. These estimates are derived from the estimation of (5) where experience is modeled as a quadratic and, where appropriate, years of job tenure and a dummy variable for having intermittent employment is included.
2. Standard errors in parentheses. These are robust standard errors with clustering on the individual.
3. The estimates of the gender gap after 5 and 10 years are based on assuming no change in job so job tenure rises with experience and the job mobility variables are zero.

**Table 6**  
**Gender Differences in Personality Among Teenagers: BHPS Data**

Percentages agreeing with the statement	Men	Women	Sample
I feel I have a number of good qualities	93.0	91.0	1,883 (1,882)
I feel that I do not have much to be proud of	13.9	17.5	1,883 (1,882)
I certainly feel useless at times	29.1	44.8	3,948 (3,753)
I am able to do things as well as most other people	91.0	90.5	1,883 (1,882)
I am a likeable person	93.0	93.6	3,948 (3,753)
I can usually solve my own problems	90.2	86.0	1,883 (1,882)
All in all, I am inclined to feel I am a failure	8.9	12.1	3,948 (3,753)
At times I feel I am no good at all	22.6	35.3	3,948 (3,753)
I feel left out of things when I am with friends	15.6	25.0	2,752 (2,679)

Notes:

1. In the final column female sample sizes are shown in the parentheses.
2. Rows 1,2,4 and 6 includes BHPS waves 9-11. Rows 3,5, and 7 includes BHPS waves 4-11. Row 9 includes BHPS waves 7-11. 'Agree' includes strongly agree and agree.

**Table 7**  
**The Gender Gap at Age 30**  
**(BCS wage data at age 30)**

	Raw Log Wage gap	Wage Gap with controls	Wage Gap evaluated at 10 yrs of actual exp with:		Sample size  Women (Men)
			Female chars	Male chars	
1. Basic equation without fertility or experience controls	0.181 (0.016)	0.163 (0.015)	0.163 (0.015)	0.163 (0.015)	3,281 (3,681)
2. Row 1 plus expected fertility controls	0.181 (0.016)	0.163 (0.015)	0.163 (0.015)	0.163 (0.015)	3,281 (3,681)
3. Row 2 plus actual experience	0.181 (0.016)	0.159 (0.015)	0.169 (0.002)	0.152 (0.002)	3,281 (3,681)
4. Row 2 plus actual full- time and part-time experience	0.181 (0.016)	0.119 (0.016)	0.127 (0.002)	0.115 (0.003)	3,281 (3,681)
5. Row 4 plus 1-digit occupation	0.181 (0.016)	0.125 (0.017)	0.121 (0.002)	0.142 (0.002)	3,281 (3,681)
6. Basic equation with sample restricted to “always in FT employment” with “no kids”	0.081 (0.025)	0.110 (0.023)	0.121 (0.004)	0.115 (0.004)	1,310 (1,589)
7. Row 5 plus 1-digit occupation	0.081 (0.025)	0.095 (0.025)	0.086 (0.005)	0.107 (0.005)	1,310 (1,589)

Notes:

1. The basic equation for each row includes controls for whether there are any children in the household, quadratic in actual full-time and part-time labour market experience, age left full-time education, quadratic for current tenure, qualifications, marital status, ethnic, establishment size, whether a supervisor and future plans for (further) children.
2. Average wage gaps are evaluated at the means of the full-time only workers.

**Table 8**  
**Gender Differences in Personality Among Children: BCS Data**

	Self-esteem		Difference in means (standard error)	Locus of control		Difference in means (standard error)
	Female	Male		Female	Male	
Age 10 scores (sample = age 10 and age 30 respondents)	-0.025	0.153	0.178 (0.028)*	0.108	0.119	0.011 (0.028)
Sample sizes	2,345	2,620		2,345	2,620	
Age 16 scores (sample = age 16 and age 30 respondents)	0.087	0.123	0.036 (0.046)	0.094	0.110	0.016 (0.042)
Sample sizes	1,111	879		1,111	879	
Sample of age 10, 16 and 30 respondents						
Age 10 scores	-0.010	0.269	0.278 (0.050)*	0.215	0.326	0.111 (0.049)
Age 16 scores	0.097	0.143	0.046 (0.053)	0.111	0.150	0.039 (0.048)
Sample sizes	835	638		835	638	

Notes:

1. \* indicates statistically significant at 1%.
2. The self-esteem and locus of control figures presented above are standardized versions of the original score variables.

**Table 9**  
**Coefficient estimates for the self-esteem and locus of control scores in the wage equation**  
**(BCS wage data at age 30)**

	Self-esteem coefficient estimates		Locus of control coefficient estimates		Sample size
	Women	Men	Women	Men	Women (Men)
1. Basic wage equation on sample of age 30 and 10 respondents plus self-esteem and locus of control from age 10	0.031 (0.014)	0.009 (0.014)	0.051 (0.016)	0.058 (0.014)	2,345 (2,620)
2. Basic wage equation on sample of age 30 and 16 respondents plus self-esteem and locus of control age 16	0.030 (0.022)	0.031 (0.023)	0.067 (0.025)	0.032 (0.027)	1,111 (879)
3. Basic wage equation on sample of age 30, 16 and 10 respondents plus self-esteem and locus of control from age 10	0.056 (0.026)	0.007 (0.030)	0.066 (0.029)	0.078 (0.031)	835 (638)

Notes:

1. The basic equation for each row includes controls for whether there are any children in the household, quadratic in actual full-time and part-time labour market experience, age left full-time education, quadratic for current tenure, qualifications, marital status, ethnic, establishment size, whether a supervisor and future plans for (further) children.
2. The sample in row 1 is BCS at age 30 merged with the BCS age 10 sample. The sample in row 2 is the BCS at age 30 merged with BCS age 16 sample. The sample in row 3 is the BCS at age 30 merged with the BCS age 10 and 16 samples.
3. Standard errors in parentheses in columns 2-5.

**Table 10**  
**Impact of self-esteem and locus of control scores on the gender gap**  
**(BCS wage data at age 30)**

	Raw Log Wage gap	Wage Gap with controls	Wage Gap evaluated at 10 yrs of actual exp with±:		Sample size  Female (Male)
			Female chars	Male chars	
1. Basic wage equation on sample of age 30 and 10 respondents	0.188 (0.019)	0.128 (0.019)	0.133 (0.002)	0.120 (0.002)	2,345 (2,620)
2. Equation and sample as row above plus self-esteem and locus of control scores from age 10	0.188 (0.019)	0.124 (0.019)	0.130 (0.002)	0.115 (0.002)	2,345 (2,620)
3. Basic wage equation on sample of age 30 and 16 respondents	0.155 (0.031)	0.083 (0.031)	0.057 (0.005)	0.048 (0.005)	1,111 (879)
4. Equation and sample as row above plus self-esteem and locus of control from age 16	0.155 (0.031)	0.083 (0.031)	0.058 (0.005)	0.047 (0.005)	1,111 (879)
5. Basic wage equation on sample of age 30, 16 and 10 respondents	0.176 (0.036)	0.110 (0.035)	0.089 (0.006)	0.096 (0.005)	835 (638)
6. Equation and sample as row above plus self-esteem and locus of control from age 10	0.176 (0.036)	0.097 (0.036)	0.082 (0.006)	0.076 (0.006)	835 (638)

Notes:

1. The basic equation for each row includes controls for whether there are any children in the household, quadratic in actual full-time and part-time labour market experience, age left full-time education, quadratic for current tenure, qualifications, marital status, ethnic, establishment size, whether a supervisor and future plans for (further) children.
2. The sample in rows 1 and 2 is BCS at age 30 merged with the BCS age 10 sample. The sample in rows 3 and 4 is BCS at age 30 merged with BCS age 16 sample. The sample in rows 5 and 6 is BCS at age 30 merged with the BCS age 10 and 16 samples.
3. Standard errors in parentheses in columns 2-5.
4. ± denotes that the average wage gaps are evaluated at the means of the full-time only workers.

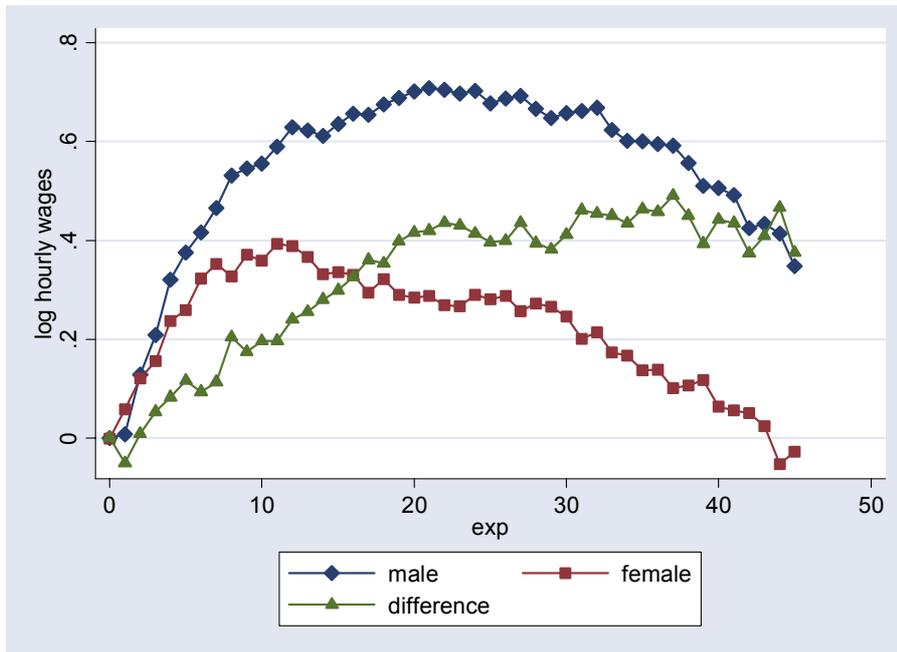
**Table A1**  
**Summary Statistics for BHPS Data**

	Young Workers	
	( $\leq 10$ yrs of potential experience)	
	Men	Women
Log Wage Growth	0.084 (0.306)	0.065 (0.278)
Potential experience (decades)	0.48 (0.28)	0.47 (0.28)
Job Tenure (decades)	0.15 (0.22)	0.13 (0.19)
Gap between wage obs	1.02 (0.18)	1.02 (0.18)
Part-Time	0.036	0.196
Training in Past Year (yrs)	0.035 (0.106)	0.030 (0.095)
Training between wage obs (yrs)	0.030 (0.090)	0.030 (0.099)
Good Move	0.254	0.231
Bad Move	0.072	0.056
Kid Move	0.0005	0.010
Other Move	0.062	0.072
Manager	0.035	0.036
Professional occupations	0.060	0.049
Associate professional	0.104	0.104
Administrative and secretarial	0.156	0.378
Skilled trades	0.239	0.022
Personal services	0.083	0.200
Sales/customer services	0.081	0.109
Machine operatives	0.094	0.037
Elementary	0.147	0.068
Graduates	0.283	0.290
'A' Level	0.396	0.430
GSEs	0.286	0.267
No qualifications	0.036	0.012
Black	0.011	0.010
Asian	0.025	0.010
Married	0.442	0.543
Child in Household	0.253	0.259
No. of kids 0-2	0.098	0.070
No. of kids 3-4	0.051	0.066
No. of kids 12-15	0.107	0.099
No. of kids 16-18	0.028	0.031

Notes.

1. Sample is those with observations on wage growth aged 16-65 with less than 45 years of potential experience. Sample numbers for wage growth are 5015 for men and 5535 for women – some variables have smaller sample sizes because of non-response.
2. Means are reported and standard errors in parentheses. Standard errors not reported for binary variables.

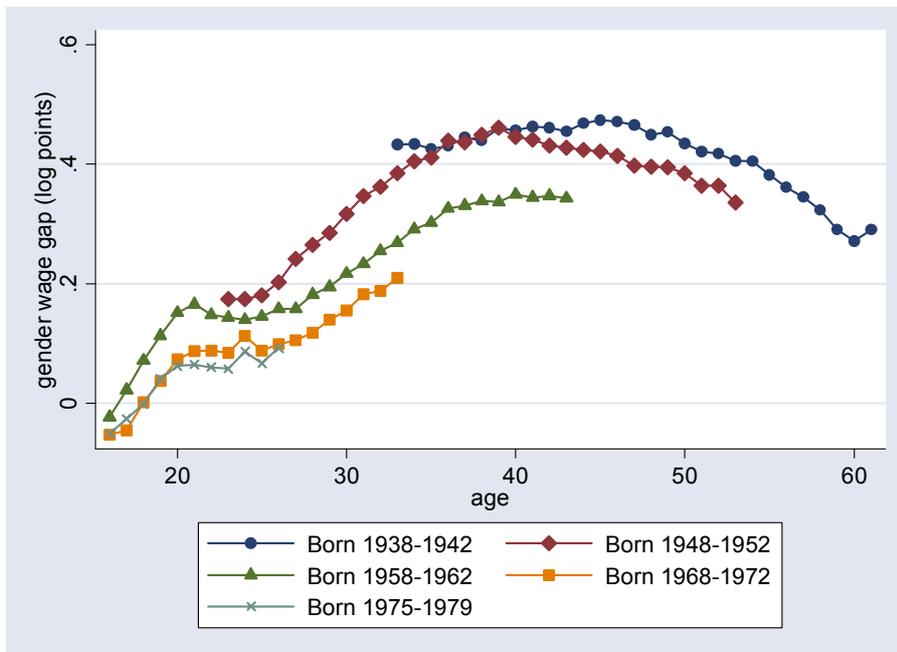
**Figure 1**  
**The Earnings-Experience Profile for Men and Women**



Notes.

1. Data come from the first 12 waves of the BHPS.
2. Log hourly wages are normalized to be zero for men with zero years of labour market experience.

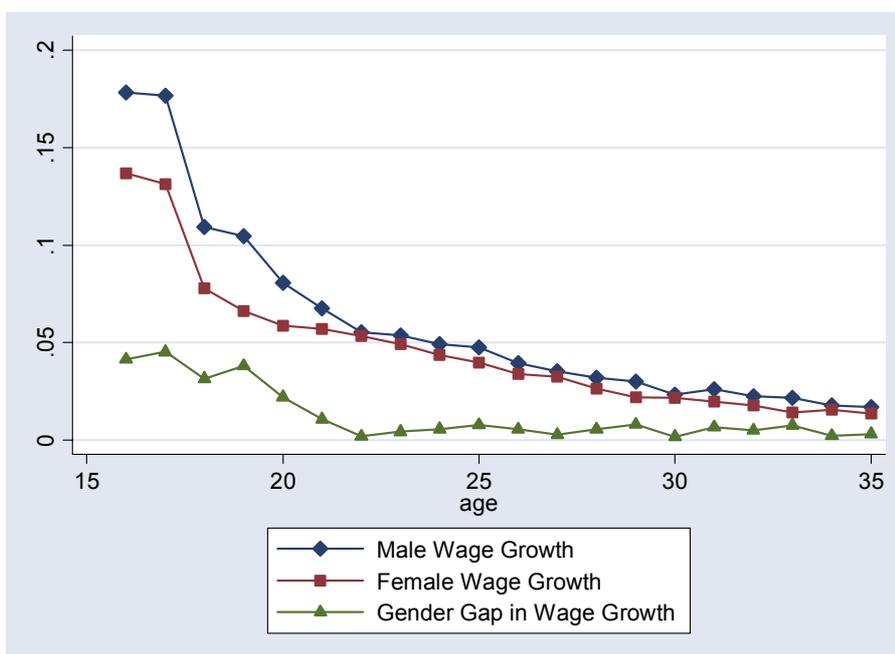
**Figure 2**  
**The Evolution of the Gender Pay Gap for Different Birth Cohorts**



Notes.

1. Data come from the New Earnings Survey, 1975-2001.
2. Earnings data are hourly earnings excluding over-time.

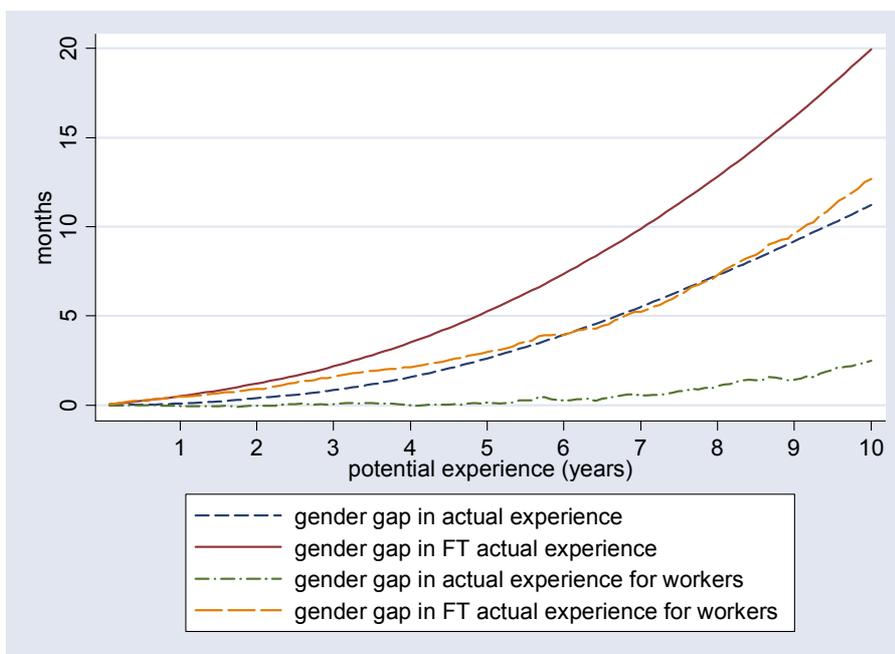
**Figure 3**  
**Gender Differences in Wage Growth: New Earnings Survey Data**



Notes.

1. The NES does not contain information on education so cannot be used to compute years of experience.
2. This is annual wage growth for the sample of workers observed in two adjacent years.

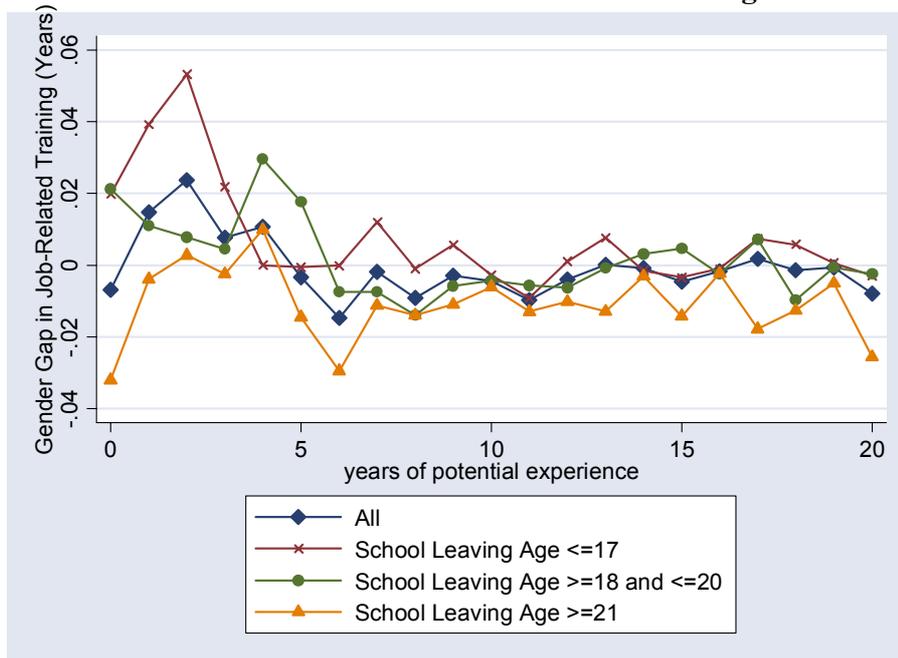
**Figure 4**  
**Gender Differences in Accumulated Work Experience**



Notes.

1. These figures come from the 1970 British Cohort Study. I would like to thank Fernando Galindo-Rueda for allowing me to use the work-history data he had constructed.

**Figure 5**  
**Gender Differences in On-the-Job Training**

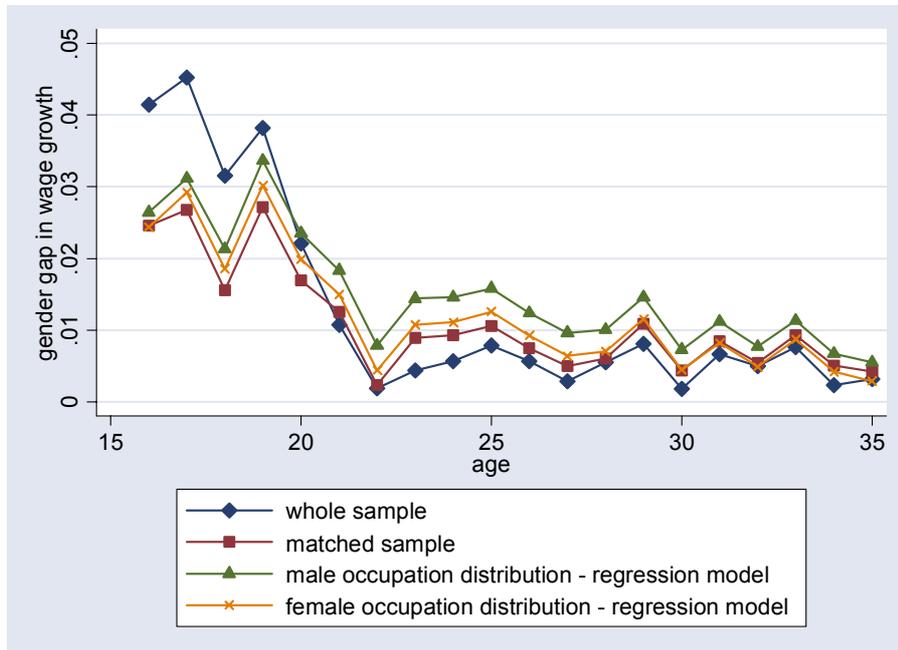


Notes.

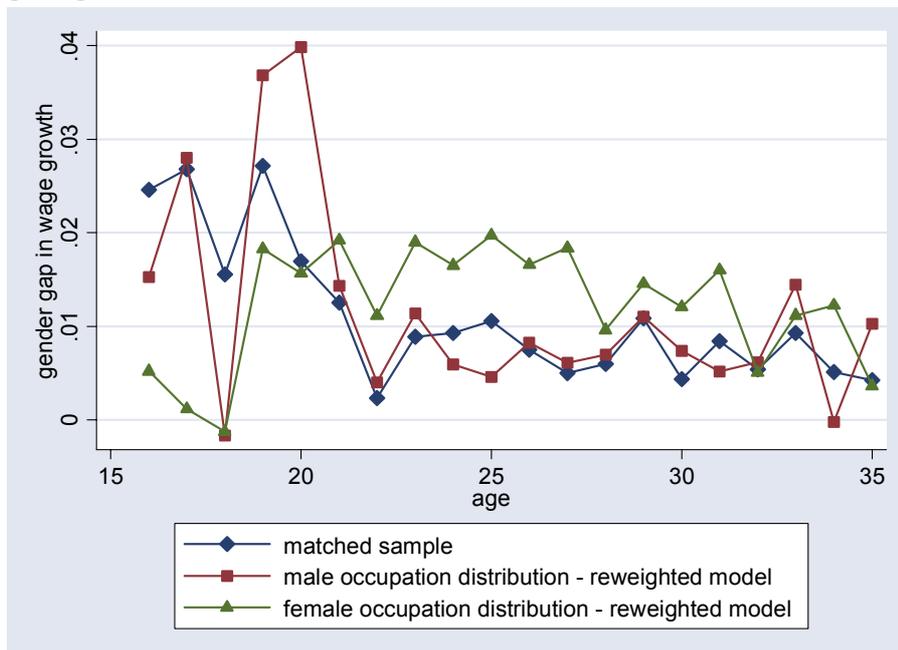
1. This data comes from the Labour Force Survey for the years 2000-2003.

**Figure 6**  
**The Impact of Occupational Job Segregation on Gender Differences in Wage Growth**

A. Regression Model



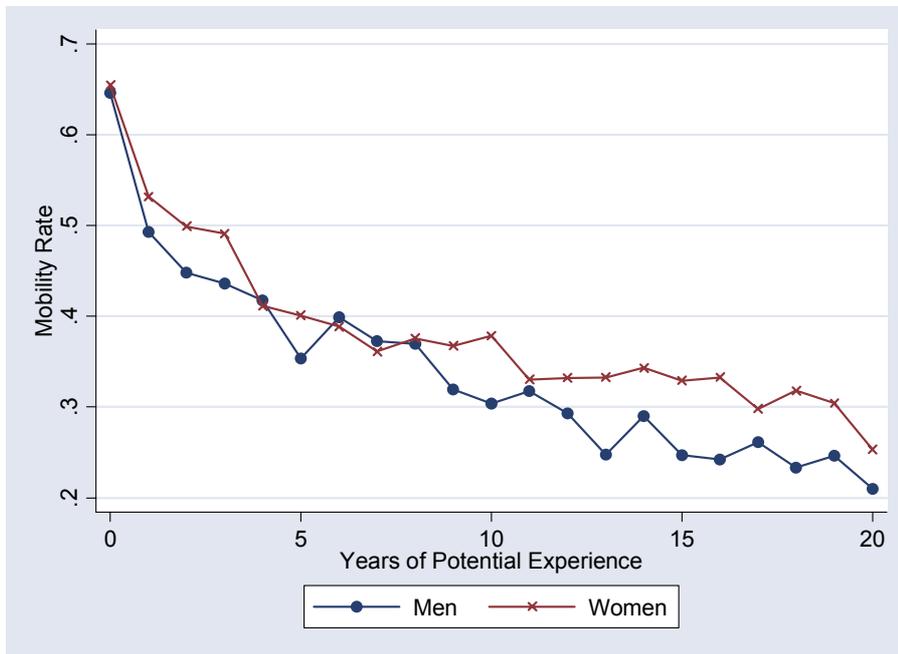
B. Reweighting Model



Notes.

1. This data comes from the New Earnings Survey for 1996-2001. Occupation is measured at the 3-digit level.
2. The matched sample is the gender gap in wage growth excluding those men and women in occupations with very low representation of the opposite sex, as discussed in the text.
3. The regression model simply includes dummy variables for each occupation in the wage growth equations. The re-weighting model reweights observations to obtain the desired occupational distribution.

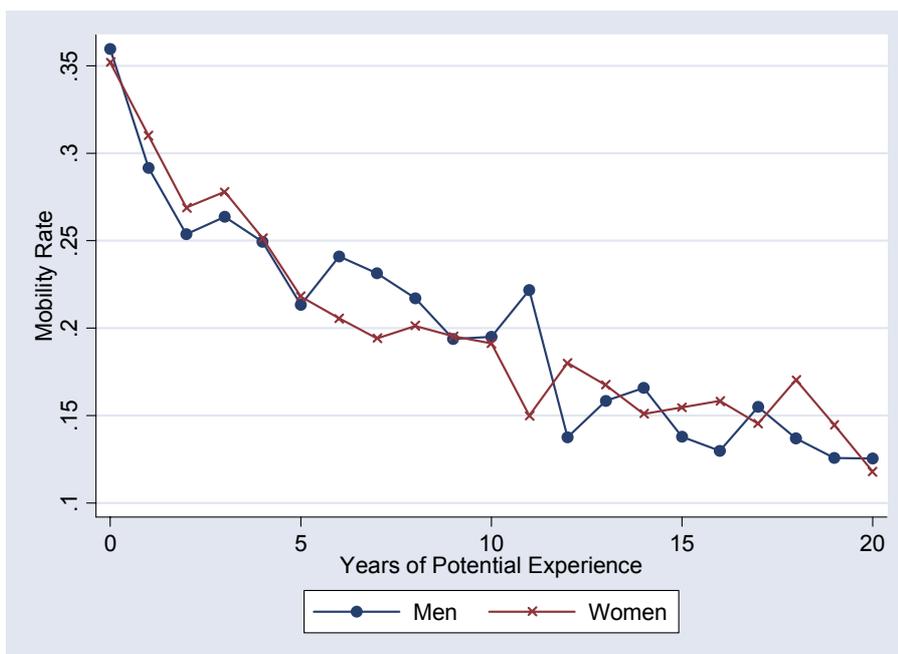
**Figure 7**  
**Job Mobility Rates: Total**



Notes.

1. These data come from the BHPS.
2. The mobility rate is measured as the fraction of workers who change jobs or leave a job for non-employment in the coming year.

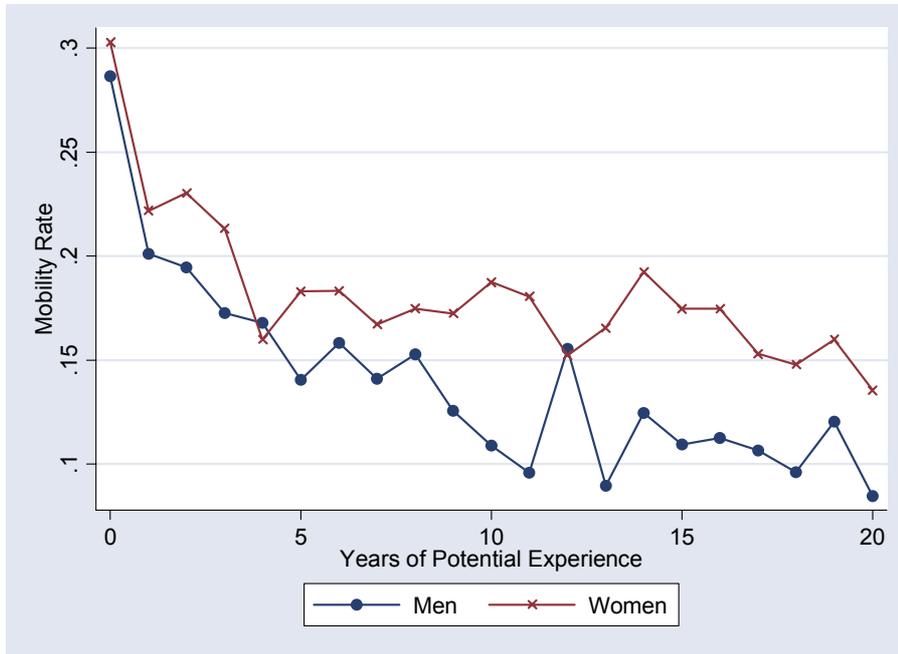
**Figure 8**  
**Job Mobility Rates: for better job**



Notes.

1. As for Figure 7 but with mobility defined as being for a better job.

**Figure 9**  
**Job Mobility Rates: not for better job**



Notes.

1. As for Figure 7 but with mobility not being defined as being for a better job.

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