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ABSTRACT

GENDER AND RACIAL DISCRIMINATION IN PAY AND PROMOTION FOR NHS NURSES*

For many years the NHS has been subject to allegations that gender and racial discrimination are a feature of the internal labour market for qualified nurses. This paper examines this issue with regard to the promotion process using 1994 survey data. We start by rejecting the assumption of covariate exogeneity inherent in the ordered probit model. A full simultaneous model is then developed which has important consequences for estimates of the influence of gender, ethnicity, training and career interruptions. We find evidence of significant differences in speed of promotion between gender and ethnic groups, which imply large differences in career earnings.

JEL Classification: C5, I1, J3, J7

Keywords: Nursing, promotions, gender, ethnicity, ordered probit models, endogeneity

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I. INTRODUCTION

Since its establishment in the post-war period, the National Health Service (NHS) in Britain has been subject to allegations that gender and racial discrimination are a feature of the internal labour market for qualified nursing staff (see Beishon et al., 1995; Davies and Rosser, 1986; Ellis, 1990; IHMS, 1995). Government concern about discrimination in the NHS has led to 'a fair process for determining reward' and 'equality of opportunity' being identified as prime objectives in the Department of Health's recent Consultancy Document 'Working Together: Securing a quality workforce for the NHS' (DOH, 1998).

Labour market discrimination, of course, is not only a characteristic of the nursing profession in Britain, but also of the labour market more generally (see, for recent evidence, Blackaby, Clark, Leslie and Murphy, 1994, 1997, Blackaby, Drinkwater, Leslie and Murphy 1997; Jones and Makepeace, 1996; Groot and Maasen van de Brink, 1996; Shields and Wheatley Price, 1999; and Wright and Ermisch, 1991). One conclusion from this literature is that pay differentials between men and women, whites and non-whites, are not fully explained by differences in their observable human capital characteristics. For example, Wright and Ermisch (1991) found, using data from the 1980 'Women in Work Survey', that less than two-thirds of the 48% earnings differential between men and women could be attributed to differences in labour market characteristics. Despite the continued existence of a significant gender pay differential in Britain,[1] the last two decades have, however, seen a considerable improvement in the relative position of women, which, in part, is attributed to the success of equal opportunities legislation introduced since the early 1970s (see, for example, Blackaby, Clark, Leslie and Murphy, 1997; Tzannatos, 1987, 1988).

On race, Blackaby *et. al.* (1994) found that non-whites, having more favourable observed characteristics should have experienced a 4.4% wage advantage over whites between 1983 and 1989, whereas the actual wage differential was 12.1% in favour of whites. In contrast to the case of gender, it is generally accepted that equal opportunities legislation has been less successful in reducing the white/non-white pay differential, with the latter group of workers becoming increasingly concentrated in the lower percentiles of the pay distribution (Blackaby et al., 1994).

Some studies have suggested that these pay differentials are largely attributable to the fact that women and ethnic minorities have lower promotion rates and are thus less likely to be found in higher paying jobs. There is then a 'glass ceiling' preventing members of disadvantaged groups from advancing to the higher levels of the occupational ladder.[2] Jones and Makepeace (1996), using personnel data from a large financial company, find some evidence that women have to meet tougher promotion criteria than men, and conclude that discrimination is evident in all promotions beyond the bottom of the job ladder. In contrast, however, Groot and Maassen van de Brink (1996), using data from the British Household Panel Survey (BHPS), find evidence to suggest a rather different discriminatory mechanism. They make a distinction between jobs in which there is potential for promotion and jobs with few prospects, and find that women are less likely to be appointed to the former. Booth et al. (1998) also use data from the BHPS, but interestingly find no significant gender differences in the probability of promotion for full-time workers. Women, however, are found to receive a lower reward to promotion than men, suggesting that, because of 'sticky floors', promotion is not a panacea for the general disadvantage faced by women in the labour market (Booth at al., 1998). This, however, is unlikely to be a feature of NHS nursing, which is still characterised by rigid pay scales.

The recent literature on gender promotion differentials has been motivated by the model of Lazear and Rosen (1991), which predicts that women must have a greater ability than men

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[1] See Blau and Kahn (1996) for international comparisons of gender wage differentials.

if they are to be promoted. This is because women generally have productive opportunities in the household that men do not, and thus have a higher risk of turnover. This reduces the expected net benefits to the firm from training and promoting women and so fewer are observed in the higher levels of the firm.

In this paper, we examine the promotion process for nurses working in the NHS in the hope of informing the debate on the workings of internal labour markets. Apart from the suggestion of discrimination in the NHS nursing labour market, the nursing occupation is an important subject of study for other reasons.[3] Firstly, demographic trends and increasing health care demands mean that nursing is an increasingly important sector of the labour market. However, it is also one in which there is a crisis of morale and recruitment (UNISON, 1996). This crisis may be linked to the NHS promotion process - only 20% of white, 13% of Black and 12% of Asian NHS nurses express satisfaction with their chances of promotion (Beishon et al., 1995). A second distinctive feature of nursing is that it is one of the 'caring' professions, where considerations other than the usual economic ones might be expected to play a role in pay and promotion. It is also a female-dominated profession, with over 90% of qualified nurses being women. A consequence is that the majority of those who make the promotion and hiring decisions are female (only 12% of nurse managers are male in our sample), and this raises questions about the origin and extent of any gender discrimination. In addition, ethnic minorities are also over-represented in nursing, with 6.3% of female nurses and 14.7% of male nurses from ethnic minorities, compared with 3.6% and 3.9% in all employment (Beishon et al., 1995). Nursing is also an unusual profession in that it is dominated by the public sector, with over 90% of working nurses in the public sector at any one time (Phillips, 1996). It is sometimes assumed that gender and racial discrimination are

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[2] See Davidson and Cooper (1992) for a thorough discussion of the concept of a 'glass ceiling'.
[3] There are, however, few econometric studies which have examined the workings of the labour market for professional nurses in Britain (see Beaumont and Elliot (1992) and Phillips (1996)). This situation contrasts with that of the US (see Holtmann and Idson (1993), Ault and Rutman (1994), Hirsch and Schumacher (1995), Krall

less significant in the public than in the private sector (see Blackaby *et al*., 1996, for evidence), and one of our objectives is to investigate that assumption in the context of nursing. Finally, nursing is a sector in which pay is negotiated at the national level and pay differentials within grades are small, and thus it can be argued that promotion is the appropriate process to study, rather than pay itself.

In order to gain reliable and robust econometric estimates of the promotion process for NHS nurses, we address a problem with earlier studies of promotion arising from the inclusion of potentially endogenously determined regressors in the promotion model. In particular, we question the assumption of exogeneity for labour market participation history, the number of training spells and part-time status - all of which would lead to biased estimates and incorrect inferences about gender and race inequalities. We start from the conventional ordered probit (OP) model, and then develop a full simultaneous model which allows for the possible endogeneity of five important features of the individual's participation and training history. The unobservable heterogeneity terms linking these variables to the promotion process is accommodated using simulated maximum likelihood (SML).

II. DATA AND SAMPLE CHARACTERISTICS

We use data from a 1994 survey of NHS nursing staff conducted by the Policy Studies Institute for the Department of Health (Beishon et al., 1995). Data were gathered from postal questionnaire responses to a one-in-three sample of the permanent nursing staff from a set of 91 NHS employers in England. Members of the ethnic minorities were deliberately over-sampled. The final response rate was 62%, generating observations on 8,178 female and 741 male State Registered Nurses (RGNs) aged between 21 and 65. A unique feature of the survey is the amount of detailed information available on work histories, allowing us to

(1995), Lane and Gohmann (1995), Ahlburg and Mahony (1996) and Schumacher (1997)).

identify actual years of nursing experience, total time spent out of nursing and the number of career breaks undertaken. Having a measure of actual experience enables us to gain more reliable estimates of the effect of experience on the promotions process, than would the use of the usual age-minus-age-left-school proxy of experience or other imputed estimates (Wright and Ermisch, 1991). This is particularly true for females, who are the majority group in nursing, though this measure of actual experience may suffer from some degree of retrospective bias. The survey also contains information on the highest level of educational achievement, the age of first registration and the number of completed post-basic training spells, as well as the usual personal and household characteristics. The definition of the variables and the sample characteristics are provided in Table A1.

The current grading structure for NHS nursing staff was introduced in 1988 and spans grades A to I. Grades A and B are unqualified auxiliary and support nurse grades and Grade C is primarily made up of State Enrolled Nurses (SENs). For RGNs, who are the focus of this paper, after completing three years of basic nurse training the starting grade is D. Grades D and E then represent core staff nurses, grades F and G are charge nurses and ward managers and grades H and I are senior nurses and nurse managers. The sample distribution of nursing grades by gender and ethnic origin (see Pudney and Shields, 1999) suggests gender and race differentials considerably smaller than those found by Jones and Makepeace (1996) and Groot and Maassen van de Brink (1996), although there is a mild tendency for a higher proportion of men than women to be at grades H and I (for example, 10.9% of white males compared to 7.3% of white females). However, crude sample frequencies are hard to interpret because of the different career paths followed by members of different groups. Indeed, Table 1, showing the mean years of actual experience and training spells by grade and gender, suggests a greater role for gender differentials, with men on average reaching the higher grades with one or two fewer years' experience than women, and slightly more episodes of training.

[Table 1 about here]

Within the NHS internal labour market, the promotion process for RGNs can best be characterised by the concept of a 'waiting time', where nurses wait for promotion opportunities whilst accumulating on-the-job experience which can be augmented by further post-basic training. As a nurse progresses up the grade structure a number of job elements become more important - the ability to work without supervision, to be an assessor, evaluator and planner of nursing needs and care, to be a researcher and teacher of nursing, and to undertake managerial responsibility. Post-basic training is voluntary and often involves some cost to the trainee.

III. A MODEL OF PROMOTION WITH EXOGENOUS PARTICIPATION AND TRAINING

Our analysis focuses on a categorical variable y, taking values 1....m for a set of m nursing grades. Other relevant and possibly endogenous variables covered by the survey are: the number of interruptions to the nursing career (censored by the survey at an upper limit of 3); the number of past training spells undertaken; the total length of time spent in non-NHS nursing since the completion of basic training; the existence of at least one period spent in the overseas or private nursing sectors; and the distinction between full-time and part-time current participation status.

To begin with, we ignore the possibility of unobservable personal characteristics which might influence grading simultaneously with these participation and training variables, and we include the variables describing the participation and training history together with other exogenous covariates in a row vector x. The discrete conditional probability function $\Pr(y|x)$ is commonly specified as an Ordered Probit model (OP). Examples in the literature on promotions include Jones and Makepeace (1996) and Winter-Ebmer and Zweimuller (1997), but the model is widely used for the analysis of ordinal data. It is based on the idea of a latent variable representing the individual's potential for career progression, assumed to be generated by the following normal regression structure:

$$y^* = x\alpha + \varepsilon \tag{1}$$

where x is a row vector of observable characteristics (including summaries of the individuals work history), α is a column vector of coefficients and ε is a normally distributed random term, with variance normalised at 1. We then assume the existence of a sequence of promotion thresholds $C_0....C_m$ from which the grade probabilities can be constructed as follows:

$$\Pr(y = g \mid x, q) = \Phi(C_g - x\alpha) - \Phi(C_{g-1} - x\alpha) \tag{2}$$

where $\Phi(.)$ is the normal distribution function. The threshold parameters are subject to the normalisations $C_0 = -\infty, C_m = +\infty$. This is the approach used by Jones and Makepeace (1996), for instance, where experience is entered via a quadratic specification.[4] We prefer to use a transformation of τ which gives a finite asymptote to the effect of experience. In other words, a given grade cannot necessarily be achieved merely through the passage of time, and this has the reasonable implication that there may be some grades that will never be reached by a given individual, no matter how much experience he or she accumulates. To achieve this, we use the following inverse transform of experience:

$$\Psi(\tau) = \min \{1, \tau^{-1}\} \tag{3}$$

The variable $\Psi(\tau)$ is trimmed at one year to avoid distortions at very short job tenures (which are rare in the sample). The trimming threshold of a year seems reasonable, and gives a better fit than alternatives of 0.5 and 2 years. We use a quadratic in Ψ rather than τ, and this leads to a better maximised likelihood in every case. After some experimentation with the choice of explanatory variables, our final estimates of the OP model are given in Table 2. Note that the small sample size for males means that we have too few observations at the two top grades for the threshold governing $\mathrm{H} \rightarrow \mathrm{I}$ promotions to estimated reliably. We have therefore merged grades H and I, and only work with 5 rather than 6 possible grades for men.

Full discussion of the results is postponed to section V. However, these simple OP estimates are consistent with *a priori* expectations. Non-white ethnic groups are associated with lower job grades, significantly so for females, but insignificantly for the smaller male sample. Education and training are both associated with higher grades, while career breaks and part-time working are linked to slower rates of progression, especially for men. Note that there is some suggestion here that it is the length of career breaks, rather than their occurrence, that acts as a handicap for women. Indeed, it is plausible to argue that experience of childcare (which often implies career interruptions) is of value in a nursing career. Marriage is estimated to have a positive impact for both men and women, but the coefficient is larger and more significant for men. However, the dominant influence on the achieved job grade is the inverse waiting time variable $\Psi(\tau)$.

[Table 2 about here]

IV. ENDOGENOUS PARTICIPATION AND TRAINING

Decisions about career breaks and training may be determined simultaneously with career progression, since there might exist common unobservable factors that influence all of these

[4] We have also estimated generalised models in which the thresholds are functions of the explanatory variables (See Pudney and Shields, 1999 for details)

observed outcomes. There are five variables which must be considered possibly endogenous in this sense. Of these, the number of career breaks and the number of training spells are all ordinal variables that can be modelled within the OP framework, and the dummies for experience of non-NHS nursing and for part-time working are modelled as binary probits. The remaining variable, the total length of career breaks, is zero for those with no career breaks and continuously distributed for others. We proceed in two stages: first we develop a score test of the exogeneity hypothesis; and then an estimator for use in the event that exogeneity is rejected. Identification is discussed at the latter stage.

(a) A Test for Exogeneity of Participation and Training History

We begin with a simple case where we are testing the exogeneity of a single explanatory variable, *w*, which is one element of the vector *x* from the latent regression (1). This variable is generated by an appropriate discrete model, estimated separately by maximum likelihood. The test is based on the covariance between the generalised residuals from the principal model of *y* and the supplementary model of x^*, where the residuals are defined as the best prediction of the value of the underlying behavioural disturbance, conditional on all observed information. The generalised residual, $\hat{\varepsilon}$, for the main job grading model is the prediction of ε conditional on the observable data; $E(\varepsilon \mid y, x)$ has the form:

$$\hat{\varepsilon} = -\sum_{g=1}^{m} \eta_g \left\{ \frac{\phi\left(\hat{C}_g - x\hat{\alpha}\right) - \phi\left(\hat{C}_{g-1} - x\hat{\alpha}\right)}{\Phi\left(\hat{C}_g - x\hat{\alpha}\right) - \Phi\left(\hat{C}_{g-1} - x\hat{\alpha}\right)} \right\} \qquad (4)$$

The hypothesis we wish to test is the following moment restriction:

$$\mathrm{H}_0 : \ E\left(\varepsilon \ \upsilon\right) = E\left\{E\left(\varepsilon \ \upsilon \mid y, x\right)\right\} = 0 \qquad (5)$$

where υ is the random disturbance underlying the auxiliary model for *w*. Under the null hypothesis, the models for *y* and *w* are conditionally independent. Using the approach of Pagan and Vella (1989), our score test statistic is:

$$t = \frac{l'm}{\sqrt{m'\left(I - D(D'D)^{-1}D'\right)m}} \tag{6}$$

where *l* is an *n* x 1 vector of ones and *m* is an *n* x 1 vector with *i*th element equal to the product of the two generalised residuals $\hat{\varepsilon}_i \hat{\upsilon}_i$. $D = \{D_1 | D_2\}$ is an $n \times (p_1 + p_2)$ matrix with *i*th row containing the derivatives of the likelihood element l_i with respect to the p_1 parameters in the principal model, followed by the derivatives of the likelihood element l_i^* with respect to the p_2 parameters of the model for *w*. Under H_0 the test statistic is asymptotically distributed as N(0,1). A χ^2 variant of the test examines the exogeneity of all variables simultaneously.

The auxiliary models used here are OP models for the number of training episodes and career breaks, binary probits for non-NHS nursing experience and part-time working, and a censored regression for the total length of career breaks. The test results are given in Table 3. Exogeneity is rejected by the overall χ^2 test applied to all five training and participation variables. The failure of exogeneity is clearest for females, where the sample size is largest. When broken into tests for individual covariates, positive t-ratios are found for the number of training spells, and this suggests the existence of unobserved factors (such as ‘motivation’ or ‘commitment’) which simultaneously cause individuals to do well in terms of promotion, and also to undertake training more readily than others. The corollary of this is that the previously-reported estimate of the effect of training spells, particularly for females, is likely to overstate the role of training *per se* as a factor in promotions.

[Table 3 about here]

Where significant, the test on individual participation variables is negative. The natural interpretation here is that there are unobservables (such as the existence of outside commitments or poor health), which are responsible simultaneously for a slow rate of promotion and an interrupted or partial history of participation. The implication here is that the OP estimates are likely to overstate the negative effects of incomplete participation, which acts in part as a proxy for these unobservable personal attributes.

(b) A Simultaneous Model with Heterogeneity

The test results in Table 3 indicate that the OP model for the promotions process will be distorted by bias unless an estimator is used which makes some allowance for the endogeneity of training and participation histories. We now estimate a generalised model involving underlying unobservable random effects. Let *w* be the 1×5 sub-vector of *x*, containing the potentially endogenous training/participation covariates. The underlying latent regression system can then be written:

$$y^* = x\alpha + \varepsilon + \gamma u^* \qquad (7)$$

$$w^* = \Gamma z + u^*$$

where w^* is the vector of latent variables underlying statistical models for the five auxiliary variables *w*, and γ is a row vector of coefficients of the unobservable heterogeneity terms. These auxiliary models are: a truncated loglinear regression for the total length of career breaks (conditional on there being at least one break); and binary probit or OP models as appropriate for the remaining four variables. The residual vector u^* is distributed as $\mathrm{N}(0, \Omega)$, where Ω is a positive definite matrix which is general except for normalisation restrictions (on all variables except for length of career breaks, whose scale is observed). We implement this general covariance structure using a factor-decomposition by writing u^* in the form Pv, where v is a vector of independent standard normal variates and P is a triangular matrix. This entails no loss of generality, but offers the possibility of giving the unobservables some interpretation, as in factor analysis. The details of the estimation of this joint model by simulated maximum likelihood can be found in Pudney and Shields (1999).

The strategy we have used to arrive at these estimates is to develop the auxiliary models separately, before estimating the full system jointly. In the smaller male sub-sample, it was not always possible to maintain a great deal of detail in the specification; this is particularly true for the indicator of part-time working, where the number of part-time males was too small to permit reliable estimation of anything but an intercept.

(c) Identification of a Simultaneous Model

The potential for identification problems with models of this kind is well known. For example, Heckman (1990) considers the following related model:

$$\begin{aligned} &y_1 = g_1(x_1) + \varepsilon_1 \\ &y_2 = g_2(x_2) + \varepsilon_2 \\ &y = dy_1 + (1-d)y_2 \\ &d^* = z\gamma + v \\ &d = 1 \quad if \quad d^* > 0 \\ &d = 0 \quad if \quad d^* \leq 0 \end{aligned} \tag{8}$$

where only y, d, x_1, x_2 and z are observed, and ε_1, ε_2, v are unobserved random errors. Heckman (1990) shows that γ, the functions g_1 and g_2 and the bivariate marginals F(ε_1, v) and F(ε_2, v) are identified nonparametrically provided z contains a continuous variable excluded from x_1 and x_2. Our model is more complex than this structure, since there are several endogenous explanatory variables, and they are not simple binary indicators. The variables excluded from our job grade model but appearing in the auxiliary models (family structure and housing tenure) are discrete rather than continuous as Heckman's result requires, and the dependent variable y is observed in coarser categorical form, not continuously as in (8). Thus there are grounds for concern over identification.

However, in the context of realistic applied work, the fully nonparametric approach to identification is often unhelpful, amounting to a counsel of perfection. Indeed, we would argue that the great majority of applied models fitted to survey data are essentially unidentifiable in the strict nonparametric sense, with or without the endogeneity problem we are considering here. For example, the fairly typical set of explanatory variables included in the ordered probit model of Table 2 contains two continuous variables (experience and age at start of career), the remainder being discrete. The discrete variables define a partition of the population into $4 \times 6 \times 13 \times 4 \times 2 \times 2 \times 2 = 9984$ cells, so a full nonparametric specification for (say) a regression on these variables would amount to a collection of 9984 bivariate regression functions. Most or all of these cells would be too sparsely observed for estimation to be feasible, for any conceivable sample size, so that such a regression is effectively unidentified in the non-parametric sense. Despite this, there is no reason why a fitted model using these explanatory variables should not give worthwhile results – all that is required is a little continuity so that a reasonably flexible specification can span the cells adequately.

Even in the case of simultaneous models, non-identification can be overcome by means of the same kind of simplifying assumptions that are built into any cross-section regression model – for example linearity in the explanatory variables and mild restrictions on the joint distribution of the error process. As an example, we consider in appendix 1 the following ordered probit with an endogenous dummy explanatory variable:

$$
\begin{aligned}
&y^* = x\alpha + \psi d + \varepsilon \\
&y \le g \qquad iff \qquad y^* \le C_g \\
&d^* = z\gamma + v \qquad\qquad\qquad\qquad\qquad\qquad (9) \\
&d = 1 \qquad if \qquad d^* > 0 \\
&d = 0 \qquad if \qquad d^* \le 0
\end{aligned}
$$

We show that the important parameters α, and ψ are identified without any need for the variables included in *z* and excluded from *x* to vary continuously, or any need to specify a particular form for the distribution of ε and *v*. Indeed, if all the elementary properties (specifically a boundary condition implied by strict monotonicity of the distribution function) of the distribution of ε and *v* are exploited fully, it is not even necessary to have exclusion restrictions on *x*. Thus the parameters of the ordered probit are identified in a semi- rather than non-parametric sense. Moreover, this result gives sufficient rather than necessary conditions for identification, so that models like (9) are over-identified in a sense, and weaker identification conditions must exist, although they are difficult to characterise in any simple way.

In fact we use exclusion restrictions (family structure and housing tenure variables do not appear in the job grade model) and a normality assumption (as a way of imposing the continuity condition) to identify the model. The full list of variables used in the auxiliary models is provided in Table A1, and the model estimates are discussed in the following section.

V. RESULTS

The estimates for the ordered probit job grading model with endogenous training and participation are provided in Table 4. The most noticeable effect of making allowance for the endogeneity of training and participation histories is a change to the estimated influence of these variables on the promotion thresholds. The estimated coefficient for training is reduced, compared to the original estimates in Table 2, and the coefficient retains its significance only for men. There is also not much less evidence of a strong negative impact of career breaks, and the estimated effect of a spell of non-NHS nursing has become significantly positive. Part-time status remains a highly significant negative influence, and its impact for men is greatly increased. If anything, the allowance for endogeneity of work history tends to increase the estimated promotion disadvantage for non-whites.

[Table 4 about here]

The estimated structure of unobserved heterogeneity is given in Table 5. In general the results show greater statistical significance for the larger female sample. However, for both cases we find that factor v_1 (associated with a propensity to engage in training) tends to increase the speed of promotion, while factors v_2, v_3 and v_5 (associated with the number and length of career breaks, and with non-NHS nursing experience) tend to retard promotion. Thus unobservable factors which interrupt NHS careers are also found to damage promotion prospects significantly.

[Table 5 about here]

(a) Implications of the results

The implications of the models we have estimated are best summarised by means of simulations of the waiting time required by different types of 'standard' nurse to achieve particular professional grades. As our base case, we take a hypothetical individual who is average with respect to most continuous characteristics and modal with respect to discrete characteristics. Specifically, he or she is married; entered nursing age 23; has O-level qualifications; works full-time; and has had no career interruptions or episodes of post-basic training. The person is also average with respect to the unobserved heterogeneity terms, ε and ν, which are set to 0. We are most interested in the effects of gender and ethnicity on the rate of promotion, so we consider six different variants: males and females, of three racial types: white, black and Asian (the other non-white category is very similar to whites, and is not separately shown). Superimposed on these 'base case' individuals, we investigate three hypothetical changes: (i) an additional 3 training episodes; (ii) two 2-year career interruptions; and (iii) an increase in 'ability' ε from the average, $\varepsilon = 0$, to the top decile, $\varepsilon = 1.2816$. Note that the first two changes correspond roughly to the sample mean values for the training and career break variables for those with non-zero values for these variables.

To indicate the robustness of the results to the endogeneity issue, our simulations use two alternative specifications: basic OP; and the full model with five training and participation variables treated as endogenous. For each model, we calculate the length of time required for any particular grade to be reached by each of the hypothetical individuals. These simulated promotion times are given in Tables 6, 7 and 8, with asymptotic standard errors.

Consider first the base case. The highest predicted grade is G, or F in the case of black or Asian females. There is a slight difference in promotion times between males and females, with men having a predicted advantage of a few months for all ethnic groups at the lowest grade E, and for whites at all grades. However, this small advantage is not statistically significantly in these cases. There is a much larger predicted advantage of around 2 years for men within the black and Asian ethnic groups. When the variable threshold version of the model is used for simulation, there is no significant estimated advantage for males.

The picture is rather different when we accept that training and participation are endogenously determined. In this situation, the biased ordered probit estimates attribute too large an influence to these variables. Since it is, on average, females who have high rates of career interruptions and low rates of training take-up, the estimated effect of female gender is correspondingly upward-biased. When the full estimator is used, these biases are corrected and, simulating the effect of gender, holding training and participation constant, we find larger predicted promotion advantages for men. At the lowest grade, men achieve promotion a year to 18 months earlier than women, depending on the ethnic group. For promotions to higher grades, the male advantage is very large, ranging from 5 to 14 years, with the difference increasing as we consider non-white ethnic groups and higher job grades. Although statistically significant, these male-female differences are subject to a high degree of sampling error, so one should not place too much weight on the point estimates.

Ethnic differences are estimated to be large and significant for all model specifications. The black and Asian groups are estimated to suffer roughly the same degree of disadvantage relative to whites. For promotion to grade E, the difference is in the range 4 months to a year or so, depending on the specification. At grade F, the difference is around 2-5 years, except for the full model for females, where the difference increases to 12-14 years, nearly doubling the time required for promotion. At the higher grade G, ethnic differences are so great for females that black and Asian women are predicted not to achieve promotion within the length of a normal career .

The impact of post-basic training episodes is explored in Table 6. The constant-threshold OP model suggests a large and significant return to training, with the simulated three training episodes reducing promotion times by around a year or so at grade $D \rightarrow E$, 4 or 5 years at grade $E \rightarrow F$, and 15 years at grade $F \rightarrow G$. However, there is a great deal of estimation uncertainty at these higher levels. The beneficial effect of training is predicted to be substantially greater for the black and Asian groups than for whites. There is no great difference between the estimated training effects for the simple OP model and the more complex simultaneous model. Therefore we do not find here that the estimates of large returns to training are invalidated by self-selection.

[Table 6 about here]

Table 7 summarises the predicted effect of two 2-year periods spent out of nursing. Note that the promotion times given *exclude* the period of the interruption itself, so that the predicted effect is additional to the 4 years lost during the simulated breaks. For men, career breaks are predicted to increase the time required to achieve any given grade. For the basic OP model, these effects are significant at the first $D \rightarrow E$ promotion hurdle. For example, a white male nurse who takes two 2-year breaks has his promotion time extended by 1.3 years, implying that it takes 4 + 1.3 = 5.3 years longer in calendar time. At higher job grades, and for all job grades in the case of the simultaneous model, there is no significant evidence of any penalty for men from career breaks.

For women the predicted impact is more complex. The basic OP model implies no significant impact of career breaks. However, the simultaneous model suggests a significant reduction in promotion times at all grades. Thus, for example, Table 7 implies that to get from grade D to E, a white female requires 3.95 years without any career breaks. With two 2-year breaks, the calendar time needed to reach grade E is extended to 3.95 + 4 - 0.44 = 7.51 years, rather than the 3.95 + 4 = 7.95 years that would be required if there were no estimated effects of career breaks. At higher grades, this predicted reduction is greater, although never significantly greater than the 4 years of the break itself. One way of interpreting this finding is to say that, for women, time spent out of nursing (usually devoted to childcare) is a good substitute for time spent in nursing. Comparison of the predictions from the full model with those from the model which makes no allowance for endogeneity is instructive: conventional estimates of the impact of career interruptions for women are not robust against the possibility of self-selection. This result gives some support to the unorthodox view that women are often *expected* to have interrupted careers, and that, when such breaks occur, they are not perceived by employers as being ‘abnormal’. Thus career breaks are less informative as a signal about the quality of an employee. However, all such interpretations are speculative, and the main point to be taken from these results is that estimates which ignore the selection problem cannot be regarded as robust.

[Table 7 about here]

The powerful effect of unobservable heterogeneity on promotion times is illustrated in Table 8. Here the years required by our ‘base case’ nurse, with average unobservable characteristics ($\varepsilon = 0$, which we term ‘average ability’), to achieve promotion to each grade are compared with a nurse with the same observable characteristics in the top decile ($\varepsilon = 1.2816$, ‘high ability’) of the distribution. Under both model variants, the required promotions times for each grade level are dramatically reduced for nurses with ‘high ability’, and for each of our groups of nurses, an additional grade is achievable within a normal career. So, whereas our ‘standard’ male nurse with ‘average ability’ was estimated to reach grade G in the latter years of his career, given a ‘high ability’ he can now reach grade H. Similarly, all three female groups grade G is now achievable rather than grade F (grade H for white females in the OP model). Moreover, the experience necessary to be promoted from grade D to E becomes effectively halved for both sexes, with the time gains for the more ‘able’ becoming progressively larger as we more higher up the grade structure. This difference in speed of promotion between nurses with ‘average ability’ and ‘high ability’ implies a considerable differential in lifetime earnings.

[Table 8 about here]

(b) Auxiliary Models

While the main focus of this paper is the job grading process, the estimates from the five auxiliary models provide a number of insights into the workings of the nursing labour market: these are presented in Appendix 2 (Tables A2 - A6). Here we focus on the results from the training and career break models. Overall, there are fewer significant influences on training and participation histories for males compared to the larger female sample. Starting with the determinants of post-basic training spells for NHS nurses, we find some degree of consistency with findings for the wider workforce (see, for example, Green, 1993; Shields, 1998). Increased years since first registration, higher general educational attainment and being an owner-occupier tend to raise the expected number of training spells, whilst having school-age children (for females) is associated with reduced training participation. Interestingly, black females are estimated to participate in significantly more training episodes than their white counterparts, but the opposite is found for Asian nurses. In contrast to the wider training literature, marriage is found to have no significant effect on the amount of training episodes undertaken.

Career breaks are positively associated with years since registration, higher educational attainment, being married and having school-age children, and negatively related with being an owner-occupier. Black nurses tend to undertake more, and Asian nurses fewer, career breaks than whites, although this is significantly so only for black females. For females nurses, time since registration tends to push-up the length of careers breaks whilst the opposite is true for males. For both sexes, white nurses undertake significantly longer career breaks than either black or Asian nurses. Higher educational attainment is positively associated with the length of career breaks (apart from males with ‘O’ or ‘A’ levels), with this relationship being generally stronger for males than females. For men, being married or an owner-occupier tends to reduce the length of career breaks, whilst having children has the opposite effect. Females who are married and who have children appear to take longer career breaks than their single counterparts, whilst having pre-school age children and being an owner-occupier are associated with shorter career breaks.

(c) Implied Earnings Differentials

Slow promotion implies low lifetime earnings under progressive salary scales with pay ceilings for each grade. To put a cash figure on the promotion disadvantage that we have found for women relative to men, and for non-whites relative to whites, we have used the 1996-7 NHS salary scales, together with the predicted promotion times given previously, to construct an estimate of total career earnings. In doing this, we have assumed that: there is no discounting; when the top of a scale is reached the salary remains at that level until promotion to a new scale takes place (with an immediate 1-increment increase); there is no change in the scales over time; the career begins at age 23 and retirement takes place at age 60; there are no career breaks, training episodes or spells of part-time work.

The simulations proceed by carrying out the following steps at each replication *r*: (i) generate a vector of pseudo-random parameter estimates $\hat{\theta}^r \sim N(\hat{\theta}, V)$, where $\hat{\theta}$ is the vector of estimated parameters of the promotions model and *V* is the asymptotic approximation to its covariance matrix; (ii) calculate the predicted promotion times to each grade, $\hat{\tau}_E ... \hat{\tau}_I^r$; (iii) use the salary scales to compute the corresponding career earnings total, E^r. Repeat this for *r* = 1 … 1000 and compute the median value and a 90% empirical confidence interval. When comparing different types of individual, the same set of underlying pseudo-random numbers is re-used to reduce simulation errors in comparisons. Note that the contrasts in Table 9 are median differences, and not differences of medians.[5]

[Table 9 about here]

Differences in total career earnings between men and women are small for the basic OP estimates, but much larger, and more significant, for the estimates which take account of the endogeneity of participation and training history. In this case the typical man gains from £35,000 to £48,000 over the course of a career, depending on his ethnic group - at the upper end of this range, this figure is not far short of the price of an average house. The earnings differential between whites and Blacks and Asians is estimated at between £52,000 and £57,000 for women using the standard OP model, but this is reduced to between £26,000 and £35,000 once endogeneity is allowed for. For men, a similar estimated difference, between £29,000 and £38,000, is implied by both models.

VI. CONCLUSIONS

Our aim has been to establish empirically the extent of gender and race disadvantage in the promotion process of NHS nurses, and to provide some evidence regarding the validity of the allegations that discrimination is a feature of the internal labour market for nursing staff. In order to gain reliable estimates of the promotion process and the degree of labour market disadvantage we have explored a possible specification problem inherent in the ordered probit model commonly used for the promotion process. We have developed a test for the exogeneity of key covariates and strongly rejected the OP model. The breakdown of the

[5] For comparison , using the estimates from the full simultaneous model, the 'base' white male nurse with 'high ability' ($\varepsilon = 1.2816$) would have lifetime earnings £99,000 (i.e. £890,000 - £791,000) higher than the same nurse with 'average ability' ($\varepsilon = 0$). The equivalent earnings differentials for white female nurses would be £139,000 (i.e. £876,000 - £737,000). The point estimates of the gender and racial lifetime earnings differential highlighted in Table 9 remain roughly the same under the 'high ability' assumption.

exogeneity assumption has serious distortionary effects on the econometric estimates which, in our case, leads to misleading inferences about the differences in the speed of promotion between gender and racial groups and consequently life-time earnings.

Despite the fact that NHS nursing is a public sector, female-dominated, 'caring' profession with a high proportion of staff from ethnic minority groups we find evidence that:

(i) After controlling for the endogeneity of participation and training history, male nurses are found to have a significant advantage in terms of speed of promotion - amounting in cash terms to between £35,000 and £48,000 in additional earnings over a whole career.

(ii) There is also clear evidence of a advantage for white over black or Asian nurses, implying a life-time earnings loss for black and Asian nurses of between £26,000 and £35,000 for females and between £30,000 and £38,000 for males.

In studies such as this, it is not generally possible to state with 100% confidence that the gender and racial disadvantage that have been identified are solely the result of labour market discrimination. Nevertheless, our findings suggests that gender and racial disadvantage is a serious cause for concern given the current low level of morale in NHS nursing, and the considerable problems being faced in recruiting female and ethnic minority school-leavers into the nursing profession and retaining qualified staff. Current government polices aimed at introducing 'a fair process of determining reward' and 'equality of opportunity' into the NHS labour market should be rigorously pursued.

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TABLE 1

Mean Years of Actual Experience and Numbers of Post-Basic Training Spells by Grade and Gender

(Standard errors in parentheses)

	Female RGNs		Male RGNs	
Grade	**Mean years of experience**	**Mean training spells**	**Mean years of experience**	**Mean training spells**
D	8.64 (0.20)	0.36 (0.02)	6.29 (0.39)	0.52 (0.09)
E	12.71 (0.15)	0.82 (0.02)	10.77 (0.48)	0.87 (0.06)
F	16.42 (0.23)	1.24 (0.03)	14.32 (0.75)	1.45 (0.10)
G	19.48 (0.18)	1.28 (0.03)	18.24 (0.52)	1.55 (0.08)
H	21.97 (0.40)	1.62 (0.06)	17.84 (1.34)	1.57 (0.19)
I	22.96 (0.71)	1.22 (0.09)	21.60 (1.22)	1.07 (0.17)

TABLE 2

Ordered Probit Estimates of Job Grading: Exogenous Participation and Training History
(Standard errors in parentheses)

Covariates	Females	Males
Experience		
$\Psi(\tau)$	-10.873	-9.864
	(0.282)	(0.784)
$\Psi^2(\tau)$	7.273	6.868
	(0.312)	(0.793)
Ethnicity		
Black	-0.324	-0.165
	(0.058)	(0.161)
Asian	-0.254	-0.175
	(0.076)	(0.133)
Other non-white	-0.000	-0.059
	(0.042)	(0.148)
Education and training		
O level	0.179	-0.174
	(0.038)	(0.127)
A level	0.360	-0.115
	(0.045)	(0.152)
ONC	0.262	0.337
	(0.061)	(0.177)
HND	0.599	0.305
	(0.047)	(0.145)
Degree	0.765	0.251
	(0.064)	(0.170)
No. of training spells	0.180	0.147
	(0.010)	(0.037)
Participation history		
No. of career breaks	0.028	-0.161
	(0.015)	(0.096)
Length of breaks	-0.018	-0.047
	(0.003)	(0.024)
Nursing outside NHS	-0.001	0.377
	(0.033)	(0.165)
Part-time	-0.445	-0.963
	(0.029)	(0.236)
Age career began / 10	0.703	0.024
	(0.156)	(0.554)
(Age career began / 10)^2	-0.100	-0.032
	(0.027)	(0.098)
Married	0.053	0.229
	(0.029)	(0.098)
No. of grades (*m*)	6	5
Sample size	8178	741
Log-likelihood	-10663.14	-931.85

TABLE 3

Exogeneity Tests

Covariate	Females	Males
Asymptotic t-statistic for ...		
Number of training spells	3.825	0.120
Number of career breaks	-8.047	-2.467
Length of career breaks	-12.676	-3.054
Non-NHS experience	-11.845	-1.262
Part-time worker	-3.964	0.593
Overall χ^2	χ^2 (5) = 250.54	χ^2 (5) = 11.928

TABLE 4

Ordered Probit Estimates of Job Grading: Endogenous Training and Participation
(Standard errors in parentheses)

Covariates	**Females**	**Males**
Actual Experience		
$\Psi(\tau)$	-10.206	-11.001
	(0.325)	(1.163)
$\Psi^2(\tau)$	6.552	7.577
	(0.352)	(1.060)
Ethnicity		
Black	-0.353	-0.263
	(0.064)	(0.205)
Asian	-0.271	-0.210
	(0.081)	(0.161)
Other non-white	-0.005	-0.064
	(0.046)	(0.187)
Education and training		
O level	0.178	-0.169
	(0.041)	(0.157)
A level	0.387	-0.051
	(0.048)	(0.183)
ONC	0.298	0.466
	(0.065)	(0.218)
HND	0.700	0.465
	(0.052)	(0.198)
Degree	0.851	0.254
	(0.070)	(0.202)
No. of training spells	0.123	0.043
	(0.022)	(0.105)
Participation history		
No. of career breaks	0.098	-0.121
	(0.026)	(0.171)
Length of breaks	0.004	-0.010
	(0.004)	(0.039)
Nursing outside NHS	0.269	0.726
	(0.059)	(0.267)
Part-time	-0.463	-1.632
	(0.052)	(0.475)
Age career began / 10	0.579	-0.056
	(0.173)	(0.668)
(Age career began / 10)^2	-0.074	-0.014
	(0.030)	(0.118)
Married	0.026	0.280
	(0.032)	(0.123)
No. of grades (*m*)	6	5
Sample size	8178	741

TABLE 5

Estimated Structure of Unobserved Heterogeneity: Estimates of γ and P

(Standard errors in parentheses)

	Females				
	v_1	v_2	v_3	v_4	v_5
Job Grade	0.154 (0.039)	-0.225 (0.036)	-0.162 (0.040)	0.037 (0.041)	-0.228 (0.030)
Number of training spells	1	0	0	0	0
Number of career breaks	-0.114 (0.025)	1	0	0	0
Non-NHS experience	-0.027 (0.040)	0.550 (0.051)	1	0	0
Part-time	-0.525 (0.039)	0.337 (0.039)	-0.074 (0.045)	1	0
Length of career breaks	-0.082 (0.021)	0.076 (0.024)	0.222 (0.024)	0.037 (0.023)	1
	Males				
Job Grade	0.222 (0.164)	-0.279 (0.164)	-0.340 (0.167)	0.107 (0.167)	-0.260 (0.153)
Number of training spells	1	0	0	0	0
Number of career breaks	-0.196 (0.119)	1	0	0	0
Non-NHS experience	0.133 (0.214)	0.079 (0.324)	1	0	0
Part-time	-0.213 (0.287)	-0.160 (0.314)	-0.571 (0.433)	1	0
Length of career breaks	0.228 (0.024)	-0.034 (0.027)	0.395 (0.021)	0.322 (0.017)	1

TABLE 6

The Impact of 3 Training Episodes on Required Promotion Times

(Standard errors in parentheses)

Type of Individual	Promotion Times D → E		E → F		F → G	
	Base	**Impact**	**Base**	**Impact**	**Base**	**Impact**
	Exogenous participation and training history					
Men						
White	3.45	-0.77	9.42	-3.21	21.94	-11.42
	(0.26)	(0.20)	(1.13)	(0.96)	(5.79)	(5.19)
Black	3.81	-0.86	11.53	-4.37	35.85	-22.70
	(0.47)	(0.23)	(2.76)	(1.83)	(24.11)	(21.12)
Asian	3.83	-0.87	11.68	-4.46	37.21	-23.87
	(0.41)	(0.23)	(2.17)	(1.62)	(19.59)	(17.79)
Women						
White	3.90	-0.95	9.82	-3.66	22.20	-12.21
	(0.08)	(0.05)	(0.33)	(0.28)	(1.71)	(1.55)
Black	4.70	-1.22	14.67	-6.69	-	-
	(0.18)	(0.09)	(1.36)	(1.00)		
Asian	4.50	-1.15	13.27	-5.76	-	-
	(0.21)	(0.09)	(1.40)	(0.97)		
	Endogenous participation and training history					
Men						
White	3.37	-0.22	9.00	-1.01	20.00	-4.06
	(0.29)	(0.52)	(1.40)	(2.41)	(6.66)	(9.67)
Black	3.83	-0.72	11.97	-3.98	40.26	-24.32
	(0.54)	(0.66)	(3.55)	(4.00)	(37.38)	(38.02)
Asian	3.77	-0.61	11.25	-3.26	33.60	-17.66
	(0.46)	(0.67)	(2.64)	(3.61)	(21.60)	(24.44)
Women						
White	3.95	-0.72	11.68	-3.84	41.42	-25.42
	(0.10)	(0.13)	(0.70)	(0.77)	(9.74)	(9.41)
Black	4.90	-1.67	20.92	-13.08	-	-
	(0.24)	(0.26)	(3.65)	(3.67)		
Asian	4.65	-1.42	17.72	-9.88	-	-
	(0.25)	(0.27)	(2.97)	(2.97)		

TABLE 7

The Impact of Two 2-Year Career Breaks on Required Promotion Times
(Standard errors in parentheses)

Type of Individual	Promotion Times D →E Base	D →E Impact	E →F Base	E →F Impact	F →G Base	F →G Impact
	Exogenous participation and training history					
Men						
White	3.45	1.30	9.42	11.30	21.94	-
	(0.26)	(0.56)	(1.13)	(8.22)	(5.79)	
Black	3.81	1.53	11.53	21.25	35.85	-
	(0.47)	(0.70)	(2.76)	(23.87)	(24.11)	
Asian	3.83	1.55	11.68	22.24	37.21	-
	(0.41)	(0.72)	(2.17)	(24.65)	(19.59)	
Women						
White	3.90	0.03	9.82	0.15	22.20	0.73
	(0.08)	(0.06)	(0.33)	(0.30)	(1.71)	(1.45)
Black	4.70	0.04	14.67	0.33	-	-
	(0.18)	(0.08)	(1.36)	(0.65)		
Asian	4.50	0.04	13.27	0.27	-	-
	(0.21)	(0.08)	(1.40)	(0.54)		
	Endogenous participation and training history					
Men						
White	3.37	0.55	9.00	3.29	20.00	-
	(0.29)	(0.72)	(1.40)	(5.12)	(6.66)	
Black	3.88	0.05	11.97	0.32	40.26	-
	(0.54)	(0.89)	(3.55)	(6.35)	(37.38)	
Asian	3.77	0.15	11.25	1.05	33.60	-
	(0.46)	(0.75)	(2.64)	(5.29)	(21.60)	
Women						
White	3.95	-0.44	11.68	-2.54	41.42	-19.63
	(0.10)	(0.10)	(0.70)	(0.67)	(9.74)	(8.76)
Black	4.90	-1.39	20.92	-11.78	-	-
	(0.24)	(0.25)	(3.65)	(3.64)		
Asian	4.65	-1.14	17.72	-8.58	-	-
	(0.25)	(0.26)	(2.97)	(2.98)		

TABLE 8

The Impact of Unobservable 'Ability' on Required Promotion Times $(\varepsilon = 0 \rightarrow \varepsilon = 1.2816)$

(Standard errors in parentheses)

Type of Individual	**Promotion Times**							
	ε = 0 (Average ability)				**ε = 1.2816 (High ability)**			
	D →E	**E →F**	**F →G**	**G →H**	**D →E**	**E →F**	**F →G**	**G →H**
	Exogenous participation and training history							
Men								
White	3.45	9.42	21.94	-	1.08	3.51	4.94	15.87
	(0.26)	(1.13)	(5.79)		(0.11)	(0.29)	(0.42)	(3.15)
Black	3.81	11.53	35.85	-	1.16	3.88	5.56	22.29
	(0.47)	(2.76)	(24.11)		(0.17)	(0.50)	(0.82)	(9.67)
Asian	3.83	11.68	37.21	-	1.15	3.90	5.60	22.82
	(0.41)	(2.17)	(19.59)		(0.16)	(0.44)	(0.69)	(7.79)
Women								
White	3.90	9.82	22.20	-	2.03	3.89	5.43	25.06
	(0.08)	(0.33)	(1.71)		(0.04)	(0.09)	(0.13)	(2.39)
Black	4.70	14.67	-	-	2.40	4.69	6.85	-
	(0.18)	(1.36)			(0.09)	(0.19)	(0.34)	
Asian	4.50	13.27	-	-	2.32	4.49	6.49	-
	(0.21)	(1.40)			(0.10)	(0.22)	(0.39)	
	Endogenous participation and training history							
Men								
White	3.37	9.00	20.00	-	1.18	3.72	5.28	19.02
	(0.29)	(1.40)	(6.66)		(0.19)	(0.38)	(0.62)	(6.83)
Black	3.88	11.97	40.26	-	1.05	4.30	6.32	36.61
	(0.54)	(3.55)	(37.38)		(0.12)	(0.70)	(1.26)	(34.96)
Asian	3.77	11.25	33.60	-	1.07	4.18	6.09	31.00
	(0.46)	(2.64)	(21.60)		(0.13)	(0.57)	(0.98)	(20.33)
Women								
White	3.95	11.68	41.42	-	2.02	4.08	5.98	-
	(0.10)	(0.70)	(9.74)		(0.06)	(0.11)	(0.21)	
Black	4.90	20.92	-	-	2.43	5.08	8.02	-
	(0.24)	(3.65)			(0.27)	(0.27)	(0.59)	
Asian	4.65	17.72	-	-	2.33	4.82	7.44	-
	(0.25)	(2.97)			(0.11)	(0.28)	(0.59)	

TABLE 9

The Earnings Consequences of Gender/Ethnicity Differences in Promotion Times for the Median of Earnings Simulated Conditional on Personal Characteristics

Ethnic Group	Salary Totals for 40-Year Career		Difference Relative to White		Difference Relative to Males
	Males	**Females**	**Males**	**Females**	**Females**
			Exogenous Participation and Training History		
White	786	783	-	-	-3
	(741 , 804)	(772 , 790)			(-24 , 41)
Black	748	726	-29	-57	-22
	(715 , 802)	(717 , 732)	(-69 , 19)	(-65 , -47)	(-76 , 11)
Asian	743	729	-34	-52	-12
	(720 , 791)	(721 , 757)	(-67 , 7)	(-93 , -25)	(-63 , 22)
			Endogenous Participation and Training History		
White	791	737	-	-	-48
	(738 , 812)	(730 , 762)			(-75 , 3)
Black	738	708	-38	-35	-35
	(705 , 805)	(682 , 721)	(-80 , 6)	(-55 , -20)	(-101 , 6)
Asian	750	717	-30	-26	-36
	(715 , 803)	(697 , 729)	(-71 , 7)	(-47 , -9)	(-90 , 3)

APPENDIX 1: Identification

Consider the following simplified model containing only a single binary endogenous explanatory variable. We follow broadly the approach of Heckman (1990), except that we assume a linear index function model.

$$
\begin{aligned}
&y^* = x\alpha + \psi d + \varepsilon \\
&y \le g \quad iff \quad y^* \le C_g \\
&d^* = z\gamma + v \\
&d = 1 \quad if \quad d^* > 0 \\
&d = 0 \quad if \quad d^* \le 0
\end{aligned}
$$

Define a sub-population $S(q)$ consisting of those with values of z such that $\Pr(d=0 \mid z) = q$, for an arbitrary $q \in (0,1)$. Then define a further sub-population $T_g(p, q)$ consisting of those for whom x is such that $\Pr(y \le g \mid x) = p$ for some arbitrary $p \in (0,1)$. Then:

$$pq = F(C_g - x\alpha, -z\gamma), \qquad x, z \in T_g(p,q)$$

and

$$q = F(+\infty, -z\gamma), \qquad z \in S(q)$$

where $F(\,.\, , \,.\,)$ is the distribution function of ε and v. F is assumed only to be strictly monotonic. These relationships can be inverted:

$$C_g = x\alpha + \Psi(pq, -z\gamma), \qquad x, z \in T_g(p,q)$$

$$-z\gamma = \Xi(q), \qquad z \in S(q)$$

Note that the binary response model for d is identifiable (subject to a normalisation restriction, so that γ and Ξ are known. Now normalise the grading model. In the ordered probit framework, this is usually done by restricting F to have zero mean and unit variance, leaving $C_1 \ldots C_{m-1}$ as free parameters, but it is more convenient here to use the normalisation $C_1 = 0$ and $C_2 = 1$ (assume m>2). Thus, picking grades g = 1, 2:

$$0 = x\alpha + \Psi(pq, \Xi(q)), \qquad x, z \in T_1(p,q)$$
$$1 = x^*\alpha + \Psi(pq, \Xi(q)), \qquad x^*, z \in T_2(p,q)$$

Our aim is to deduce the value of the vector α and the form of the unknown function Ψ. Note that $x\alpha$ is constant over $T_1(p, q)$ and $x^*\alpha$ over $T_2(p, q)$. Now vary p and q. For each (p, q) choose a pair (x, x^*) from $T_1(p, q) \times T_2(p, q)$. Then:

$$1 = (x^* - x)\alpha, \qquad x \in T_1(p,q);\ x^* \in T_2(p,q)$$

It is possible to solve uniquely for α if it is possible to find a set of vectors forming the rows of a matrix $\mathbf{X}$-$\mathbf{X}^*$ such that rank($\mathbf{X}$-$\mathbf{X}^*$) = k, where k is the number of explanatory variables in x. If z contains a variable (ζ say) excluded from x, then this is clearly possible, since $z = (x, \zeta)$ and thus $x\gamma_x = -\Xi(q) + \zeta\gamma_\zeta$ and there is no exact collinearity in x for any q. Note that, in this linear setting, it is not necessary for the excluded variable ζ to be continuously-distributed. Once α has been found in this way, it is possible to construct Ψ uniquely as the value $x\alpha$ at each p, q on the unit square. F can then be recovered by inverting Ψ.

A problem appears to arise when z contains no variables excluded from x. It is then possible to write $-x\gamma_x = \Xi(q)$ for each q, and thus:

$$\begin{aligned} C_g &= x\alpha + \Psi(pq, -z\gamma) \\ &= x(\alpha - \lambda\gamma) + \left(\Psi(pq, \Xi(q)) - \lambda\Xi(q)\right) \end{aligned}$$

for any arbitrary number λ. Thus, the following equation:

$$1 = (x^* - x)a, \qquad x \in T_1(p,q);\ x^* \in T_2(p,q)$$

is satisfied by any vector of the form $a = (\alpha - \lambda\gamma)$, with a corresponding infinity of choices for Ψ, each of the form Ψ-$\lambda\Xi$. Ψ and α thus appear unidentified, as a consequence of the collinearity of x induced by the condition $\Pr(d=0 \mid z) = q$.

However, this argument does not use all the information we have about the unknown distribution F. In particular, we know that there exists a finite $M(p)$ such that $\lim_{v\to\infty} F(M, v)$

$= p$, for any $p < 1$. Thus $\lim_{q\to 1} \Psi(pq, \Xi(q)) = M(p) < \infty$ and $\lim_{q\to 1} \Xi(q) = +\infty$. This implies that a function of the form $\Psi(pq, \Xi(q)) - \lambda\Xi(q)$ has an infinite limit for any choice of λ other than zero, whereas $\Psi(pq, \Xi(q))$ is known to have a finite limit. Thus, our knowledge of the limiting behaviour of F is sufficient to resolve the apparent identification problem induced by the collinearity of x when there are no exclusion restrictions. Note that this identification result is only available in the linear setting. When seen in this light, the value of making a specific assumption about the distribution of (ε, v) is not that it imposes a particular shape on the function F, but rather that it is a convenient way of building into the estimation procedure the identifying boundary conditions. This interpretation is consistent with the common finding that empirical results are often insensitive to specific distributional assumptions (Mroz, 1987; Newey et al., 1990).

Once α and F have been identified in this way, then $C_3 \dots C_{m-1}$ can be recovered from the equations $pq = F(C_g - x\alpha, -z\gamma)$, and the coefficient of the endogenous explanatory variable, ψ, from the analogous equation for $\Pr(y \leq g, d=1 \mid x, z)$. Indeed, there is a substantial degree of over-identification, which stems from the linearity assumption. The extension of this result to the case of multiple discrete endogenous explanatory variables is straightforward.

APPENDIX 2: Sample characteristics and estimates of auxiliary models

TABLE A1 ***Sample Characteristics***

(Standard errors in parentheses)

Mean of Variable	Females	Males
Job Grading Model		
Actual years of experience (excluding career breaks)	15.371	13.502
	(0.10)	(0.31)
Black	0.048	0.074
	(0.002)	(0.009)
Asian	0.024	0.116
	(0.002)	(0.012)
Other non-white	0.086	0.091
	(0.003)	(0.011)
O level	0.451	0.310
	(0.005)	(0.017)
A level	0.212	0.166
	(0.005)	(0.014)
ONC	0.050	0.078
	(0.002)	(0.010)
HND	0.133	0.195
	(0.008)	(0.014)
Degree	0.042	0.096
	(0.002)	(0.011)
Number of training episodes	1.001	1.115
	(0.013)	(0.040)
Number of career breaks	1.110	0.298
	(0.011)	(0.021)
Length of breaks (years)	2.146	0.525
	(0.039)	(0.057)
Non-NHS nursing experience	0.167	0.099
	(0.009)	(0.014)
Currently working part-time	0.354	0.0303
	(0.005)	(0.006)
Age when nursing career began	23.442	25.753
	(0.049)	(0.190)
Married	0.747	0.723
	(0.005)	(0.016)
Auxiliary Models		
Years since first registration	15.556	12.090
	(0.111)	(0.302)
Married with children	0.352	0.431
	(0.005)	(0.180)
Pre-school children	0.198	0.232
	(0.004)	(0.150)
School-age children	0.395	0.462
	(0.005)	(0.018)
Good childcare facilities at work	0.043	0.047
	(0.002)	(0.004)
Owner-occupier	0.864	0.755
	(0.004)	(0.016)

TABLE A2 *Ordered Probit Estimates for the Number of Training Episodes*
(Standard errors in parentheses)

Covariates	Females	Males
Age career began / 10	1.485	-
	(0.070)	
(Age career began / 10) ^{2}	-0.386	-
	(0.018)	
Time since registration / 10	1.485	1.358
	(0.070)	(0.237)
(Time since registration / 10) ^{2}	-0.386	-0.388
	(0.018)	(0.073)
Black	0.186	-
	(0.079)	
Asian	-0.284	-
	(0.104)	
Other non-white	0.087	-
	(0.058)	
O level	0.120	0.212
	(0.055)	(0.184)
A level	0.314	0.627
	(0.062)	(0.219)
ONC	0.442	0.368
	(0.085)	(0.250)
HND	0.893	1.113
	(0.066)	(0.193)
Degree	0.608	0.423
	(0.090)	(0.275)
Married	-0.021	-0.101
	(0.041)	(0.153)
Pre-school children	-0.207	-
	(0.032)	
School-age children	-0.270	-
	(0.021)	
Childcare facilities	-0.053	-
	(0.087)	
Owner-occupier	0.135	0.203
	(0.055)	(0.169)
C1	0.387	0.854
	(0.345)	(0.231)
C2	1.505	1.955
	(0.346)	(0.236)
C3	2.619	3.147
	(0.346)	(0.244)
C4	3.494	4.245
	(0.348)	(0.279)
C5	4.022	5.231
	(0.350)	(0.435)

TABLE A3 *Ordered Probit Estimates for the Number of Career Breaks*
(Standard errors in parentheses)

Covariates	**Females**	**Males**
Age career began / 10	1.286	1.229
	(0.281)	(1.649)
$(\text{Age career began} / 10)^2$	-0.293	-0.295
	(0.052)	(0.325)
Time since registration / 10	1.623	1.421
	(0.799)	(0.367)
$(\text{Time since registration} / 10)^2$	-0.170	-0.242
	(0.020)	(0.111)
Black	0.198	0.242
	(0.078)	(0.306)
Asian	-0.122	-0.489
	(0.089)	(0.267)
Other non-white	-0.082	-0.408
	(0.058)	(0.292)
O level	0.033	0.386
	(0.055)	(0.247)
A level	0.156	0.383
	(0.064)	(0.304)
ONC	0.074	0.102
	(0.090)	(0.397)
HND	-0.197	0.432
	(0.067)	(0.272)
Degree	0.113	0.955
	(0.094)	(0.328)
Married	0.209	0.219
	(0.045)	(0.203)
Married with children	-0.079	-
	(0.047)	
School-age children	0.733	0.025
	(0.048)	(0.075)
Childcare facilities	0.114	-
	(0.092)	
Owner-occupier	-0.220	-0.469
	(0.055)	(0.202)
C1	3.062	3.539
	(0.379)	(2.106)
C2	4.799	5.071
	(0.381)	(2.099)
C3	6.225	-
	(0.382)	

TABLE A4 *Loglinear Regression for the Length of Career Breaks*
(Standard errors in parentheses)

Covariates	Females	Males
Age career began / 10	-0.251	-0.536
	(0.299)	(0.447)
(Age career began / 10) ^{2}	0.052	0.206
	(0.059)	(0.091)
Time since registration / 10	1.020	-0.843
	(0.080)	(0.106)
(Time since registration / 10) ^{2}	-0.066	0.386
	(0.018)	(0.033)
Black	-0.269	-0.623
	(0.064)	(0.077)
Asian	-0.299	-0.612
	(0.093)	(0.080)
Other non-white	-1.057	0.075
	(0.053)	(0.081)
O level	0.113	-0.022
	(0.049)	(0.070)
A level	0.128	-0.353
	(0.058)	(0.089)
ONC	0.168	0.189
	(0.087)	(0.094)
HND	0.072	0.309
	(0.062)	(0.079)
Degree	0.130	1.077
	(0.086)	(0.089)
Married	0.003	-0.220
	(0.045)	(0.050)
Married with children	0.070	-
	(0.047)	
Children	-	0.138
		(0.022)
Pre-school children	-0.130	-
	(0.056)	
School-age children	0.019	-
	(0.046)	
Childcare facilities	-0.016	-
	(0.075)	
Owner-occupier	-0.138	-0.148
	(0.055)	(0.052)
Constant	-0.707	0.661
	(0.380)	(0.537)
σ	0.655	0.120
	(0.016)	(0.015)

TABLE A5 *Probit Model for Non-NHS Nursing Experience*
(Standard errors in parentheses)

Covariates	**Females**	**Males**
Age career began / 10	0.919	2.818
	(0.434)	(3.510)
(Age career began / 10)^2	-0.173	-0.502
	(0.080)	(0.663)
Time since registration / 10	0.723	0.480
	(0.139)	(0.897)
(Time since registration / 10)^2	-0.146	-0.142
	(0.033)	(0.268)
Black	0.267	-0.729
	(0.123)	(0.629)
Asian	-0.168	0.413
	(0.194)	(0.650)
Other non-white	-0.018	-0.717
	(0.097)	(0.690)
O level	0.456	0.367
	(0.092)	(0.522)
A level	0.463	-0.174
	(0.105)	(0.650)
ONC	0.535	0.690
	(0.152)	(0.860)
HND	0.332	0.278
	(0.115)	(0.577)
Degree	0.171	-0.575
	(0.157)	(0.759)
Married	-0.289	-0.289
	(0.078)	(0.429)
Married with children	0.163	-
	(0.086)	
Children	-	-0.165
		(0.166)
Pre-school children	-0.527	-
	(0.095)	
School-age children	-0.285	-
	(0.084)	
Childcare facilities	-0.208	-
	(0.135)	
Owner-occupier	-0.232	-0.732
	(0.098)	(0.398)
C1	-2.739	-3.548
	(0.596)	(4.690)

TABLE A6 *Probit Model for Part-Time Status*
(Standard errors in parentheses)

Covariates	**Females**	**Males**
Age career began / 10	0.349	-
	(0.342)	
$(\text{Age career began} / 10)^2$	-0.016	-
	(0.059)	
Time since registration / 10	0.719	-
	(0.108)	
$(\text{Time since registration} / 10)^2$	-0.006	-
	(0.027)	
Black	-1.254	-
	(0.120)	
Asian	-0.588	-
	(0.134)	
Other non-white	-0.225	-
	(0.085)	
O level	0.318	-
	(0.079)	
A level	0.352	-
	(0.092)	
ONC	0.201	-
	(0.138)	
HND	-0.466	-
	(0.100)	
Degree	0.008	-
	(0.136)	
Married	0.790	-
	(0.075)	
Married with children	0.042	-
	(0.063)	
Children	-	0.243
		(0.128)
Pre-school children	1.406	-
	(0.069)	
School-age children	0.658	-
	(0.063)	
Childcare facilities	0.381	-
	(0.106)	
Owner-occupier	0.117	-
	(0.087)	
C1	-3.996	-3.127
	(0.491)	(0.427)