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# The labour supply of nurses in the UK: evidence from the British Household Panel Survey

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# The labour supply of nurses in the UK: Evidence from the British Household Panel Survey*

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### Abstract

This paper investigates the determinants of the labour supply of nurses in the UK. Attention focuses on the elasticity of hours of work supplied with respect to wage rates. This is achieved using nine waves of data from the British Household Panel Survey. The panel nature of this survey allows us to control for individual unobserved heterogeneity thus reducing the problems encountered in models of labour supply caused by omitted variable bias. We account for the endogenous nature of wages by using 2-stage least squares. Tests for and control of selection bias are achieved using methods based on variable addition tests for panel data. We find that the elasticity of hours supplied with respect to wage is 0.40 suggesting that moderate increases in nurse hours supplied could be achieved by increases in wage rates.

**JEL codes I1 C1**

**Keywords**: Nurses, Labour supply, Wages, Panel data.

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# 1 Introduction

The determinants of the labour supply of nurses and midwives in the UK is an important area of research for informing National Health Service (NHS) labour policy decisions. Nurses and midwives make up the largest proportion of the UK NHS workforce. In 2000, the NHS employed 346,180 whole time equivalent nurses, midwifery and health visiting staff in England (Department of Health, 2001). This group represents approximately 43% of NHS Hospital and Community Health Services staff. The associated nurse pay bill for 2001/02 has been estimated to be £7.5 billion (Department of Health et al., 2001). Staff have been given a central role in achieving the modernisation agenda in the NHS. The *NHS Plan* (Department of Health, 2000) which sets out the Governments' priorities for the NHS to 2003-04 recognises that a major constraint on the capacity of the NHS to deliver the modernisation agenda is the need to increase staff numbers, including the need for an extra $20,000$ nurses.

The Government's strategy for nursing and midwifery highlights the need to introduce new roles and ways of working for nurses and midwives to improve the quality of care delivered to patients and to ensure the NHS can recruit, retain and motivate sufficient numbers of staff. New working arrangements include family friendly working practices, greater staff involvement in decision-making, better working conditions, and using the skills of staff more effectively (Department of Health, 1999, 2000). A modernised pay system is a key feature of the new working arrangements (see: A Modernised NHS Pay System, Department of Health, 2002). The key elements of current proposals include increases in basic pay, provision for additional pay for staff working in high cost areas, payments to aid recruitment and retention, standardised arrangements for overtime payments and payments for working outside normal hours and on-call duties. While these policy interventions may have the desired effect, surprisingly there is little research evidence specific to the labour market supply decisions of UK nurses from which to draw inspiration.

Antonazzo et al. (2002) provide an up-to-date review of the empirical literature on the labour supply of nurses (also see Elliott et al., 2003). The majority of studies reviewed are based on research conducted in North America. Relatively few studies, particularly those focusing on the labour supply response to own wage rates, have been conducted in the UK. The findings of their review present an unclear picture of the determinants of nurse labour supply. The authors attribute this, in part, to differences in methods of estimation, the nature of the sample data used, model specification and selectivity issues arising out of measurement error and omitted variable problems. In particular, the impact of own wage on hours worked is ambiguous as the studies reviewed revealed considerable differences over the sign, size and statistical significance of this relationship.

A study by Phillips (1995) represents the first major attempt to model empirically the labour supply response to wage rates of nurses in Britain. The approach adopted focused on the determinants of both nurse labour market participation and hours of work supplied. Discontinuities in the supply curve were also investigated. While the elasticity of the probability of participation with respect to wage is reported to be relatively high at 1.4, the elasticity of hours supplied with respect to wage was found to be small at 0.15[1]. Evidence of some discontinuities in the supply function were reported. The results suggest that rates of pay are likely to prove to be an effective policy tool for influencing the participation rate of nurses (at least while participation rates allow room for response), but less so for influencing the number of hours supplied. However, the survey data used (Women and Employment Survey, 1980) are dated and unlikely to be relevant to modern working practices in the NHS. Further, the sample size available was small at 312 observations.

More recently Skåtun et al. (2002) have studied the labour market supply of British qualified female married or cohabiting nurses and midwives. There work draws upon data from the Quarterly Labour Force Survey over the years 1999-2000. The sample consisted of 1248 females possessing a nursing qualification. Of these 1043 were working nurses and 205 were out of the labour force. The determinants of nurse labour force participation was assessed using a logit model whilst a selection bias corrected OLS model was estimated for hours of work. Both models included predicted wages in an attempt to purge the estimates of endogeneity and measurement error bias. The results indicate that both nurse labour force participation and hours of work are inelastic with respect to own wages, wage of partner and non-labour income. The elasticity of participation and hours of work with respect to own wage were 0.55 and 0.34 respectively suggesting wage policies will have a moderate effect on nurse labour supply.

[1] The elasticity cited appears to refer to the elasticity of hours of work with respect to the logarithm of wages. This translates to an elasticity of hours of 0.25 with respect to wages.

Further evidence to suggest that wage policies may not be an effective policy tool to increase the labour supply of nurses in Britain is presented by Frijters et al. (2003). Using longitudinal data from the Quarterly Labour Force Survey the authors investigate the determinants of the quitting behaviour of nurses in the NHS. Single and competing-risks duration models are used to determine the characteristics of nurses who leave the NHS workforce, highlight the importance of pay in this decision and track the destination of these workers. While the effect of wages is found to be statistically important, the predicted impact of an increase in wage rates on retention is reported to be small. The authors suggest that employers need to identify and address aspects of the job other than pay that are driving nurses' decisions to quit the NHS.

In this paper we investigate the labour market supply response of UK nurses to, among other things, hourly wage rates. This is achieved using nine waves of data from the British Household Panel Survey (BHPS). The richness of information provided in this survey allows us to control for a wide range of confounding factors when estimating the determinants of labour supply. In addition, the panel nature of the dataset allows us to control for individual unobserved heterogeneity thus further reducing the problem caused by omitted variable bias. We account for the potential endogenous nature of wages in a model of labour supply by using two-stage least squares. This also allows us to control for potential measurement error present in the wage rate variable, due, for example, to misreporting pay. Our sample consists of females who were observed at one or more of the nine waves of the BHPS to be employed as a nurse or midwife, or who held a nursing qualification. However, there is likely to be a selection process driving the decision to participate or not in the labour market and if so whether or not to work as a nurse. Restricting our estimates to females currently employed as nurses will lead to biased estimates of wage elasticities should selection effects be present and not adequately accounted for. Tests for and control of selection bias for panel data are achieved using a method proposed by Wooldridge (1995).

## 2 Models and Estimation methods

We adopt a typical static specification of labour supply (for example, see Mroz, 1987) where hours of work are related to the wage rate, other sources of income, and a set of control variables. We modify this empirical specification to account for the potential impact of sample selection and the panel nature of our data. The following model is used:

$$H_{it}^{*} = \delta ln(W_{it}) + X_{1it}\beta + Z_{1i}\gamma + \mu_i + \epsilon_{it}, \quad i = 1, 2, \ldots, N, t = 1, 2, \ldots, T_i. \tag{1}$$

where $i$ indexes individuals and $t$ indexes time periods. $H_{it}$ is the usual monthly hours of labour supplied by individual $i$ in year $t$. $ln(W_{it})$ is the logarithm of hourly wages, $X_{1it}$ is a vector of time varying regressors including income from other sources and $Z_{1i}$ is a vector of time invariant regressors. $\mu_i$ is an individual specific and time invariant unobserved error component, and $\epsilon_{it}$ is a classical mean zero disturbance.

$\delta$, $\beta$ and $\gamma$ are comformably dimensioned vectors of parameters associated with the regressors. Interest focuses on the value of $\delta$.

We also specify the following empirical nursing labour selection model:

$$S^*_{it} = X_{2it}\eta + Z_{2i}\lambda + \nu_{it} \quad i = 1, 2, \ldots, N, t = 1, 2, \ldots, T. \tag{2}$$

where

$$\begin{aligned} H_{it} = H^*_{it}, \quad S_{it} &= 1 \quad \text{if} \quad S^*_{it} > 0 \\ H_{it} \quad \text{is not observed}, \quad S_{it} &= 0 \quad \text{if} \quad S^*_{it} \leq 0 \end{aligned}$$

Here $H^*_{it}$ is the nurses observed usual monthly hours of work. The binary variable $S_{it}$ indicates whether the individual was working as a nurse (or midwife) at time $t$ ($S_{it} = 1$) or not working as a nurse ($S_{it} = 0$). $X_{2it}$ and $Z_{2i}$ are vectors of time-varying and time-invariant regressors respectively with elements common to those contained in $X_{1it}$ and $Z_{1i}$.[2] To aid identification, $X_{2it}$ and $Z_{2i}$ contain additional regressors specific to the selection equation. Details of these are provided in section 3. $\eta$ and $\lambda$ are conformably dimensioned vectors of parameters to be estimated. $\nu_{it}$ is an unobserved error disturbance. For ease of exposition we assume a balanced panel for the selection equation. This can be relaxed without loss of generality.

The sample selection problem arises because the hours of work variable $H^*$ is

[2] For obvious reasons, $X_{2it}$ and $Z_{2i}$ do not contain regressors of $X_{1it}$ and $Z_{1i}$ that are observed only for $S_{it} = 1$.

observed only for those with $S_{it} = 1$, that is, for those individuals within the sample that were working as nurses (or midwives) at time $t$. Estimation of (1), conditional on $S_{it} = 1$ has the potential for sample selection bias should the sub-sample for whom $S_{it} = 1$ differ systematically from those for whom $S_{it} = 0$.

Wooldridge (1995) describes computationally simple tests for selection bias in linear unobserved variance components panel data models which contain an observable binary selection indicator. The methods are based on variable addition tests of the empirical equation of interest (here, labour hours supplied). These require either Tobit residuals or inverse Mills ratios obtained from probit estimation of a selection equation for each time period, $t$. This is followed by a within-groups estimation of the empirical equation of interest and a test of the restriction that the coefficient on the inverse Mills ratio (or the Tobit residuals) is equal to zero. The method has a number of attractive features. In particular, it allows the unobserved individual effects in both the labour supply and selection equation to be correlated with the observed variables and that the idiosyncratic error in the labour supply equation is not required to have a known distribution and may contain arbitrary serial dependence of unspecified form (Wooldridge, 1995).[3] The method relies on normality of errors in the selection equation[4] together with a linear conditional mean indepen-

[3] Tests for selection bias in linear random effects panel data models have also been proposed but require stronger distributional assumptions concerning the unobserved individual specific effects and the idiosyncratic errors in both the empirical equation of interest and the selection equation, for example, see Verbeek and Nijman (1996) and Vella (1998).

[4] In addition, if it is assumed that the individual unobserved effect is correlated with the time varying variables then following Chamberlain (1984) this can be represented by specifying the conditional mean of the individual effect as a linear projection on the leads and lags of the observed variables.

dence assumption in the empirical equation of interest.[5] We adopt Wooldridge's approach for testing and correcting for selection bias in our model of nursing supply. The application of his method is described below.

For convenience we adopt notation similar to Wooldridge so that, in the unbalanced case, the fixed effects or within-groups model of (1) may be written as:[6]

$$\tilde{H}_{it} = \delta \widetilde{ln(W)}_{it} + \tilde{X}_{1it}\beta + \tilde{\epsilon}_{it} \qquad i = 1, 2, \ldots, N, \quad t = 1, 2, \ldots, T_i. \tag{3}$$

where, $\tilde{X}_{1it} = S_{it}X_{1it} - T_i^{-1}\sum_{t=1}^{T} S_{it}X_{1it}$ and similarly for $\widetilde{ln(W)}_{it}$ and $\tilde{\epsilon}_{it}$. In the absence of selection bias ordinary least squares (OLS) applied to (3) is an unbiased and consistent estimator of $\delta$ and $\beta$.

In the presence of an observable binary selection indicator Wooldridge proceeds to a test for selection bias by undertaking probit estimation, for each $t$, of the selection equation (2).[7] From these inverse Mills ratios for $S_{it} = 1$ can be obtained as $\hat{\lambda}_{it} = \frac{\phi(D\Gamma)}{\Phi(D\Gamma)}$ where $\phi(\cdot)$ is the standard normal density, $\Phi(\cdot)$ is the cumulative distribution function and $D\Gamma$ is the linear index obtained from the probit regressions. The wave-specific inverse Mills ratios can then be stacked by $i$ and $t$ to form an additional regressor to be inserted into the empirical labour supply model. The test

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[5] In the presence of selection, such that the idiosyncratic error, $\epsilon_{it}$, in the empirical labour supply model (1) is correlated (with coefficient $\rho$) with the error, $\nu_i$, in the selection equation (2), conditional mean independence implies that $E\left(\epsilon_{it}|\mu_i, ln(W_i), \tilde{X}_i, \nu_{it}\right) = E\left(\epsilon_{it}|\nu_{it}\right) = \rho_t \nu_{it}$. where $\tilde{X}_i = (X_{1i}, X_{2i}, Z_{1i}, Z_{2i})$ with $X_{1i} = (X_{1i1}, \ldots, X_{1iT_i})$ and similarly for $X_{2i}$ and $ln(W_i)$. That is, $\epsilon_{it}$ is mean independent of $\mu_i$, $ln(W_i)$ and $\tilde{X}_i$ conditional on $\nu_{it}$. In addition, the regression of $\epsilon_{it}$ on $\nu_{it}$ is assumed to be linear. Wooldridge shows how these assumptions can be adapted to the case where only a binary indicator is observed.

[6] Note that for the within-groups estimator, the parameter vector $\lambda$ is not estimable. This is of little concern for the empirical application presented here as the primary function of $Z_{1i}$ is to act as control variables.

[7] It is assumed here that $\nu_{it} \sim N(0, \sigma_t^2)$.

then consists of $OLS$ estimation for $S_{it} = 1$ of:

$$\tilde{H}_{it} = \delta \tilde{ln(W)}_{it} + \tilde{X}_{1it}\beta + \rho\tilde{\lambda}_{it} + \tilde{\epsilon}_{it} \qquad i = 1, 2, \ldots, N, \quad t = 1, 2, \ldots, T_i. \qquad (4)$$

where $\tilde{\lambda}_{it} = S_{it}\hat{\lambda}_{it} - T_i^{-1}\sum_{t=1}^{T} S_{it}\hat{\lambda}_{it}$, and testing $H_0 : \rho = 0$. Under the null hypothesis, OLS standard errors are unbiased.

To allow the individual unobserved effect in the selection equation $\upsilon_i$ (where $\nu_{it} = \upsilon_i + \varepsilon_{it}$) to be correlated with $X_{2it}$, we parameterise $\upsilon_i$ by assuming it is a linear combination of the within-group mean of $X_{2it}$ and a mean zero normally distributed disturbance $c_i$ such that, for each $i$ (see for example, Mundlak (1978)),

$$\upsilon_i = \pi_0 + \bar{X}_{2i.}\pi + c_i \qquad (5)$$

where $\bar{X}_{2i.} = T^{-1}\sum_{t=1}^{T} X_{2it}$ and $c_i$ is independent of $\bar{X}_{2i.}$.[8] Probit estimation is then performed for each $t$ on the reduced form selection equation obtained from inserting (5) into (2).

The above exposition assumes that the labour market selection decisions of individuals are observed for $T$ time periods and that hours of work are observed for $T_i$ periods. To maximise the data available to this study individuals' labour market decisions are observed across $T_{1i}$ periods and their hours of worked for $T_{2i}$ where $T_{2i} \leq T_{1i}$.

[8] An alternative parameterisation of $\upsilon$ is suggested by Chamberlain (1984) who assumes that the correlation between $\upsilon_i$ and $X_{2it}$ operates through the time-specific components of $X_{2it}$. This is a less restrictive assumption than that imposed in (5) and is obtained by replacing $\bar{X}_{2i.}\pi$ with $X_{2i1}\pi_1 + \cdots + X_{2iT}\pi_T$. However, Chamberlain's approach is only applicable in situations where a balanced panel is available.

The models presented above assume that wages are exogenous with respect to the idiosyncratic error, $\epsilon_{it}$, in the labour supply model (1). This is unlikely to be the case. To control for the potential endogeneity of wages we implement two-stage least squares (2SLS). In the first stage log hourly wages are regressed on the set of variables $X_{1it}$ and $Z_{1i}$ in addition to a vector of instruments. The second stage consists of regressing the hours of work equation (1) replacing log wages with predictions from the first stage regression and making appropriate corrections to standard errors. Tests of overidentifying restrictions implied by the choice of instruments are provided by the Sargan test (see for example, Wooldridge, 2002).

Our estimation strategy is as follows. We first estimate the model by *OLS* under the assumption of no selection bias. If this assumption is valid and the errors are uncorrelated with the regressors then *OLS* is unbiased and consistent. However, it will be inefficient as the errors are correlated within individuals. Secondly, under the same assumption we estimate the within-groups regression. The within-groups estimator is unbiased and consistent as $N$ and/or $T \rightarrow \infty$ even if $\mu_i$ is correlated with the regressors. However, it is likely to be inefficient. Further, the within-groups estimator will be biased and inconsistent if any regressor is correlated with the idiosyncratic error term, $\epsilon_{it}$. Thirdly, we explicitly test for sample selection using the method proposed by Wooldridge (1995) and outlined above. Finally, to account for the endogenous nature of the wage rate variable, two-stage-least squares versions of the above three estimators are implemented.[9]

[9] See Baltagi (2001) for a review of panel data models with endogenous regressors.

# 3 Data

## 3.1 The British Household Panel Survey

We use data from the British Household Panel Survey (BHPS). The BHPS is used due to its panel nature and because it consists of a rich source of information on socio-demographic, economic and occupational characteristics together with data on labour market status. (refer to Taylor, 2000) for a detailed documentation of the BHPS). The BHPS is a longitudinal survey of private households in Great Britain (England, Wales, and Scotland), designed as an annual survey of each adult (16+) member of a nationally representative sample of more than 5,000 households, with a total of approximately 10,000 individual interviews. The first wave of the survey was conducted between the 1st September 1990 and 30th April 1991. The same individuals are re-interviewed in successive waves (years) and, if they split from their original households, are also re-interviewed along with all adult members of their new households. The authors thus hope that the sample should remain broadly representative of the population in Britain. The sample for wave two onwards consists of all eligible adults in all households where there is at least one interview at wave one. We use data on individuals who provided valid responses to the variables described below in at least one of the first nine waves (collected between 1991 and 1999) of the BHPS.

The focus of attention in this study is the labour supply of female nurses. Male nurses are excluded since the nature of their labour supply decisions are likely to differ markedly from females.[10] Our basic working sample consists of all females who were observed at one or more of the 9 waves of the BHPS to be employed as a nurse or midwife, or who held a nursing qualification. Thus our basic working sample consists of 524 females for whom we have a total of 2401 observations over the nine waves available. Of these, 237 females were not observed to be employed as a nurse or midwife in any of the nine waves of BHPS data. Accordingly, 962 observations on 287 nurses and midwives were available for OLS estimation of the labour supply models. Due to the necessity to observe two or more waves of data to identify nurse specific effects, the data were reduced to 160 nurses and 835 observations for fixed effects estimation.

### 3.2 Dependent variables

A measure of labour supply was constructed as the number of hours worked per week (HRSWK) from two questions contained within the BHPS. Firstly, respondents were asked the number of hours they normally worked per week excluding overtime. The question asked: " Thinking about your (main) job, how many hours, excluding overtime and meal breaks, are you expected to work in a normal week?". This was combined with the response to a question about the number of hours paid overtime worked in a normal week. Two questions were asked of respondents. The first asked "How many hours overtime do you usually work in a normal week?". The second question asked "And how much of that overtime is usually paid overtime?".

[10] There are few male nurses in the BHPS sample.

The three questions were asked if the respondent did paid work the week prior to interview, or if they did no paid work in the week prior to interview but had a job that they were away from and the respondent was an employee.[11]

The BHPS does not contain a pre-constructed hourly wage variable and this was constructed as follows. Usual gross monthly pay (including overtime) derived from the main job of a respondent was divided by an estimate of the usual monthly hours worked (again including overtime). The variable available in the BHPS (PAYGU, Taylor et al., p558, 2000) measures the usual monthly wage or salary payment before tax and other deductions in the current main job for employees based on the respondents last payment.[12] A potential problem with this method of computing hourly wage rates is that if individuals are paid an overtime premium, then those individuals who commit to overtime work will, using our construction, be observed to receive a greater average hourly wage than those who do not. Hence, estimates of the impact of a variable on wages will be confounded, to some extent, with the impact on labour supply, as measured by overtime working. Approximately 5% of the working sample had their responses to the gross monthly pay variable imputed.[13]

[11] The relevant questions in the BHPS are JBHRS, JBOT and JBOTPD (Taylor et al., p338-339, 2000).

[12] If last gross payment was said to be the "usual", this was used. If last gross pay was missing, but net pay was present, and this was given as "usual", then gross pay was estimated from net pay, in the light of information about marital status, partner's activity, and pension scheme membership. If last payment was not the "usual" then the answer to a separate question about "usual" payment was used if given gross. If "usual payment" was given net, then this was converted to gross payment as per above (Taylor et al., p558, 2000).

[13] The imputation was performed using a combination of 'hot-deck' and regression procedures (predictive mean matching). First, to obtain values for variables used in the regression imputation a hot-deck procedure was used. This splits the sample into cells found to be predictive of the variable to be imputed, and then takes a random observation from a non-missing donor cell who matches the recipient individual in the characteristics used to partition the sample. The recipient receives the value observed for this randomly chosen donor individual. In the regression stage a regression analysis is performed, with recipients receiving the *actual value* of a non-missing donor observation.

Usual monthly hours worked was obtained by multiplying the usual weekly hours worked by 4.33. The natural logarithm of the constructed hourly wage rate is labelled LNWAGE.

This method of computing an hourly wage rate is not ideal and is likely to suffer from measurement error. For the working sample only 41% of cases were reported to have recorded wages supported by wages slips seen by the interviewer.[14] Further, since no directly measurable hourly wage rate is available in the BHPS and has to be computed, any errors in measurement in hours worked will be transmitted to the construction of hourly wages. However, the advantages of using the BHPS are that it contains rich information on potential confounding variables such as non-labour income, income of other members of household, place of work, number of children in household, etc.. Further, the use of panel data allows us to control for individual heterogeneity, and to implement better instrumental variable procedures when estimating nursing supply decisions. The problems associated with measurement error in hourly wages are mitigated by the use of 2SLS estimation procedures. In the absence of more exact measures of hourly wages we feel the benefits of using the BHPS outweigh the potential shortfalls.

The donor is determined as the individual whose predicted value deviates least from the predicted value of the recipient. Of course the value of these procedures is dependent on the extent to which the observed and missing individuals deviate according to unobserved characteristics. If they do not deviate (individuals are non-systematic non-reporters), this method will not introduce any bias. In the absence of an explicit selection-correction method within the estimation procedure of the model, imputation is likely to be superior to the exclusion of cases with missing values even if the imputation is imperfect.

[14] However, the distribution of hourly wages and weekly hours worked for nurses for whom pay slips were not seen by the interviewer were very similar to the the corresponding distributions for nurses reporting wages supported by pay slips.

### 3.3 Explanatory variables

Most empirical studies of nursing labour supply have found negative associations between a spouse's wage and household non-labour income with hours of work and labour force participation. However the size and significance of reported effects varies considerably.[15] In this study we include the respondents' non-labour income (NLBINC) together with a derived variable representing total other household income (HHINC). The latter is computed by subtracting the respondents labour and non-labour income from annual household income. Both these variables have been deflated by the retail price index.

We include an indicator of marital or cohabiting status (MARCOUP). It may be expected that due to substitutability of time, married or cohabiting females are able to devote more time, *ceteris paribus*, to non-labour market activities. This may be particularly prominent during child-bearing years (see for example, Smith, 1980). Furthermore, married/cohabiting individuals may be able to select into/out of labour force participation on the grounds of comparative advantage in market and household production. This option is not available to single individuals. Hence, we expect a negative effect of marital status on labour supply decisions.

The number and age distribution of children have been found empirically to be important for determining the labour supply of married women. The presence of preschool-age children may induce greater household demand for home-produced goods and mother's time. Further, household demand for mother's time is likely

[15] Refer to Antonazzo et al. (2002) for a summary of these effects.

to increase with the number of children. However, it has also been argued that as the number of children in the household increases, the services of older children are likely to be substituted for those of the mother in the production of home goods so that there is a tendency, at a certain point, for the mother's supply of market work to increase (see for example, Cain, 1966). We include a vector of variables which capture the age distribution of children in the household: NCH04 - number of children aged between 0 and 4 years; NCH511 - number of children aged between 5 and 11 years and NCH1218 - number of children aged between 12 and 18 years. Home productivity effects are also likely to be relevant to females who are responsible for the care of other adults in the home (Sloan and Richupan, 1974). Accordingly, we also consider whether the respondent lives with someone who is sick, handicapped or elderly for whom the respondent provides care (CARERHH).

The BHPS allows us to distinguish between nurses and midwifes working in hospitals and nursing homes, medical practices, nursing agencies and private nursing, and other medical care institutions. To control for the diversity of opportunities different employers and work environments provide we include two dummy variables.[16] The first indicates employment in a hospital or nursing home (HOSPHOME) and the second indicates private sector and agency employment (PRIVAGEN). These are contrasted against a baseline of other nursing workplace. We also control for seniority by including a dummy variable indicating whether the nurse has manage-

[16] For example, Disney and Gosling (1998) found, using the BHPS, that public and private sector pay differs, particularly for women and Phillips (1995) notes that employment opportunities, particularly opportunities for flexibility in hours worked vary across place of employment.

rial or supervisory duties (MANSUP). A dummy variable is included to distinguish midwives from nurses (MIDWIFE).

A recent study by Askildsen, Baltagi and Holmås (2002) emphasises the importance of including contractual information in models of the labour supply of health personnel. In their empirical analysis of the labour supply of Swedish nurses, they conclude that omitting information on shift work biases estimates of the wage elasticity. This is on the grounds that nursing contracts of employment in Sweden specify working conditions including standard hours of work and any compensation that may arise for work outside of normal working hours. They interpret the negative coefficient on their shift variable[17] in the hours of work equation as representing the degree of burden by working shifts. In this study, we include a vector of dummy variables representing the time of the day the respondent usually works. These were formed from the responses to the question: "Which of the categories on this card best describes the times of day you usually work?" From these the following dummy variables were constructed: respondent usually works in the evening or at night (NGHTWRK: response categories: evenings only and at night), respondent varies their work (VARWRK: response categories: both lunchtimes and evenings, other times of the day, varies with no pattern, daytime and evenings, and other) or has rotating shift work (ROTAWRK: response category: rotating shifts). These are contrasted against a baseline of daytime work (response categories: mornings only, afternoons only, during the day).

[17] The shift variable is defined as the share of monthly income that is bonus due to late, night and weekend duties.

Noting that the wage equation relates the *real* wage to human capital and other variables, we follow Grossman (1974) and Harkness (1996) by including a vector of regional dummies to account for regional price variation. The sign of the coefficients on these dummies should reflect the sign of the deviation from national average prices.[18] However, given the structure of pay in the NHS, we would expect to observe little variation in wages across geographical locations with the exception of London due to a 'London weighting allowance' to reflect the increased cost of living. Region of residence may also affect preferences and opportunities for work and as such are also included in the labour supply equations.

As exogenous time-invariant variables, we include an indicator of ethnic status which is equal to one if the individual is white and zero otherwise (WHITE).

We allow for a quadratic function of age and experience in the wage equation by including both the levels of these variables and their squares (AGE, AGESQRD, EXP, EXPSQRD). Age should capture general labour market tenure effects over and above those captured by experience. Experience is calculated as the number of years in which an individual has been doing the same job with their current employer. Conditional on age, this variable captures the effect of within-job tenure and specific (on-the-job) training. Following Mincer (1974), we expect positive coefficients for the levels of each of these variables. Mincer's model also predicts that the amount of time devoted to investment in on-the-job training should decline over the life-cycle, and hence we expect a quadratic function in experience. Similarly, we expect a

[18] If the labour market is geographically segmented, these coefficients could also reflect overall labour market disequilibrium due to low geographic mobility.

quadratic function in age. We also include the number of weeks employed in the year of interview (WKSEMP) to capture additional effects of labour market tenure and experience not ascribed to the variables described above. Age is also used in determining the participation decision and amount of labour supplied.

Following Harkness (1996), we include a variable that measures the number of employees at the individual's place of work (JBSIZE).[19] Further, we include two dummy variables to reflect the fixed costs of labour supply. The costs of childcare arrangements act as a barrier to labour market participation and where childcare facilities are provided free of charge, individuals may be willing to accept a lower wage rate than those for whom childcare is provided at a cost. These putative effects are captured by two dummy variables (CAREFREE) and (CAREPAID) that are contrasted against no childcare.

As an indicator of educational attainment we follow the categorisation of Harkness (1996) and split the sample into groups with a degree or higher (DEGHDEG), a higher national diploma or certificate of teaching qualification, or 'A' levels or equivalent (HNDALEV), and 'O' levels or CSE or equivalent (OCSE). The baseline category consists those with no formal qualifications.

We also include as an instrument in the wage and selection equations, the within BHPS sample regional labour market participation rate (PARTRATE). It is hypoth-

[19] Harkness (1996) used the original categorical coding of this variable available in the BHPS. To reduce the quantity of dummy variables in our analysis, we created a continuous variable by taking the midpoint of each category for each individual. For those who could not report the category into which their establishment fell, but were able to report whether it was above or below a particular value, we estimated their observation as a weighted average of the midpoints of the relevant categories. The weights used are the proportions of the relevant sub-sample which are in the relevant categories.

esised that higher participation rates will be related to higher wage rates. Further to aid identification in the selection equation we include a dummy variable representing the employment status of the individual in the year previous to the study wave year (LEMPLOY). We hypothesis that this variable is endogenous with respect to the individual unobserved effect in the selection equation and as such parameterise the individual effect as a function of the within-group mean of this variable as suggested by equation (5). Finally, we include a vector of time dummies to control for aggregate productivity effects and inflation.

Summary statistics for the samples used in the hours of work, wage and selection equations are presented in Table 1. Table 1 also indicates which variables are used in each of the three equations. For example, while the labour force participation rate in the region of residence is assumed to affect nurses' decisions to work and the wage rate, it is not assumed to affect the number of hours supplied. Summary statistics for the time dummies and region of residence are suppressed to conserve space.

The average reported weekly hours worked including overtime is 32.74. This accords well with other studies of the labour supply of nurses in the UK: Skåtun et al. (2002) using data from the Quarterly Labour Force Survey report an average of 31.84 hours, while Phillips (1995) using data drawn from the Women and Employment Survey of 1980 reports a sample average of 30.0. The average logarithm of reported gross hourly wage is 2.01 which is lower than the 2.22 reported by Skåtum et al. (2002).[20] However, the latter relies on data from 1999-2000 while the average reported in Table 1 is taken over the period 1991-2000. The comparable figure for the logarithm of hourly wages averaged across the 161 nurses in the ninth wave of the BHPS is 2.17.

The average age of respondents was 37 and approximately 73% worked in a hospital or nursing home. Very few nurses (approximately 1%) were employed in the private sector or by an agency. The majority (38%), reported the times of day usually worked were based on a rotational system, 35% reported working during the day, 17% during the evening/night and 10% reported varied times of work. 72% had some supervisory or managerial responsibilities.

## 4 Results

Table 2 presents the results of the estimated effects of wages, socio-economic and household composition on labour supply while Table 3 presents the reduced form estimates for the logarithm of wages. To conserve space the results of the nine cross-section selection equations are not provided here but are available from the author upon request. As the focus of this paper is the effect of wages on hours of labour supplied we concentrate discussion of the results to those presented in Table 2. The first column of results reports OLS estimates, the second column reports fixed effects (FE) results, while column three presents estimates derived from a fixed effects regression including a correction for sample selection (FE+SS). Columns four

[20] Phillips (1995) reports an average logarithm of hourly wages of 0.66 but the data used relates to 1980 and hence are not comparable to those reported in Table 1.

to six report two-stage least squares counterparts of columns one to three.

Age has a positive effect in the OLS, FE and FE+SS models. The effect is significant for the FE and FE+SS model only. However, in the models that account for the endogeneity of wages the effect of age is negative and significant. Further the effect is convex suggesting that nurses work shorter hours as they become older but to a diminishing degree. The estimated effects of household variables are as expected. Married or cohabiting nurses work less hours on average than single nurses, although the effect is significant at the 5% level only for the FE+SS estimator. There is a clear gradient across the effect of children on hours supplied with nurses with children aged under 5 (NCH04) working less hours than those with children aged 5 to 11 (NCH511) who in turn work less hours than nurses with children aged 12 to 18 (NCH1218). Non-labour income is negatively related to hours worked and is significant at the 5% level in all models except FE-2SLS and FE-2SLS+SS models. Similarly other household income is negatively related to labour supply and significant for the OLS and 2SLS models. Ceteris parabus, non-whites appear on average to work less hours than whites. In general nurses who care for others in the household supply less hours of work but the effects are significant at the 5% level only for the OLS and 2SLS estimators.

Nurses working at night (NGHTWRK) generally report lower hours than respondents who report working times that vary (VARWRK), or rotating shift work (ROTAWORK) or the baseline category of daytime work. The effects are significant at the 5% level in all models. Whilst a positive coefficient for rotating shift work is observed for all estimators, implying greater hours supplied compared to the baseline of daytime work, it is significance only for the 2SLS estimates. Managers and supervisors (MANSUP) are estimated to work longer hours compared to staff nurses in the OLS, FE and FE+SS models with the effect being significant for the later two estimators. However, once the endogeneity of wages is accounted for the direction of the estimated effects becomes negative and non-significant. For all estimators there is some indication that midwives (MIDWIFE) work less hours than nurses all other things being equal. However, the estimated effect is non-significant in all models except 2SLS.

The first row of Table 2 reports the estimated coefficients on the logarithm of hourly wages (LNWAGE). The OLS estimate is negative and non-significant at the 5% level. Should the unobserved individual specific effect be positively correlated with wages then we can expect the OLS estimate of the wage effect to be biased upwards. Controlling for unobserved heterogeneity using the FE estimator results in a reduction in the estimated impact of wages on hours supplied. The coefficient estimate is $-4.4$ and is significant at the 0.1% level.[21] The results reported in the third column indicate sample selection bias. The estimated coefficient of the inverse Mills ratio is three times greater than its standard error. However, correcting for selection bias has a modest impact on the estimated coefficients of the explanatory variables of interest. In particular, the impact on the coefficient of hourly wages is

[21] However note that the OLS estimates are not directly comparable to the FE estimates due to the difference in sample size. The OLS estimate of LNWAGE obtained on the same sample used for fixed effects estimation is 0.123 with standard error of 0.824.

small and negative.

The above models assume hourly wages to be exogenous to hours worked. This is unlikely, particularly given the construction of the wage rate variable. The results reported in columns four to six of Table 2 were obtained using two-stage least squares counterparts of the OLS, FE and FE+SS estimators. All models pass the Sargan test of over-identifying restrictions imposed by the choice of instrument set. The results of the first-stage regression of the logarithm of hourly wages (LNWAGE) on exogenous explanatory variables are reported in Table 3.[22] Age has a positive but diminishing effect on hourly wages while nurses working in a hospital or nursing home (HOSPHOME), in general, command lower wages than nurses working in other environments. More senior nursing staff (MANSUP) command higher wages. Somewhat surprisingly, the results indicate that for these data, nurses working for agencies or working in the private sector (PRIVAGEN) are associated with lower hourly wage rates. This appears contrary to expectation and is likely to be due to data anomalies in the small number of agency/private sector workers within the sample.

In general, all instruments appear with the expected sign and are significant at at least the 5% level in the OLS model. A clear gradient across educational status is observed with increased attainment associated with increased wages. These effects are highly significant. Due to collinearity with the individual unobserved effects highest

[22] Note the overidentifying restrictions in the labour supply equation is implied by the set of instruments: DEGHDEG, HNDALEV, OCSE, EXP, EXPSQRD, JBSIZE, WKSEMP, CAREFREE, CAREPAID, PARTRATE and time dummies.

educational attainment does not appear in the set of instruments for fixed effects estimation. The estimated coefficients on experience (EXP and EXPSQRD) imply the expected concave relationship with the logarithm of hourly wages using OLS. While these variables control for the effect of within-job tenure, current year general labour market tenure (WKSEMP) also exhibits a positive association with wages. The effect of the latter remains significant once individual heterogeneity has been controlled for in the fixed effects estimations. The impact of the number of employees in the workplace (JBSIZE) is also significantly related to increased hourly wages in the OLS model, but becomes non-significant using fixed effects estimation. The fixed costs associated with childcare arrangements (CAREFREE and CAREPAID) appear jointly significant at the 5% level. The estimated coefficients associated with free childcare provision are negative, potentially reflecting the lower fixed costs of labour market entry. The corresponding OLS estimate for paid childcare is positive and non-significant but negative and significant using fixed effects. Areas with high regional labour market participation rates are associated with higher hourly wages.

Accounting for the endogenous nature of wages has a profound effect on the estimated labour supply decisions. For all models the estimated coefficient on the predicted logarithm of wage is positive and highly significant. Further, controlling for unobserved heterogeneity in both the wage and hours supplied equation using fixed effects (FE-2SLS) results in a greater estimated effect of wages compared to the two-stage least squares model of column 4.[23] In the final column of Table(2)

[23] The 2SLS estimate of LNWAGE using the same sample as FE-2SLS is 8.677 (1.834). However, this model fails the Sargan test; $\chi^2_{17} = 30.69, p = 0.022$.

we observe a negative but non-significant sample selection effect resulting in a slight reduction in the effect of wages on hours of labour supplied.

The final row of Table 2 reports the elasticity of weekly hours of work with respect to wage. Again these are presented with respective standard errors in parentheses. Reflecting the sign of the coefficients on LNWAGE, elasticity estimates from models which assume exogenous wages are negative implying that higher wages are associated with lower hours worked. Once the endogenous nature of wages is accounted for within a 2-stage least squares framework, the elasticities become positive and are significantly different from zero at the 1% level. The elasticities range from 0.29 for 2SLS to 0.40 for FE-2SLS. Accordingly, we could expect a 10% increase in wages to lead to a 4.0% increase in hours worked.[24]

## 5 Conclusions

This paper investigates the determinants of the labour supply of nurses in the UK with particular attention focused on the elasticity of hours of work supplied with respect to hourly wages. This is achieved using nine waves of data from the British Household Panel Survey (BHPS). The panel nature of this survey allows us to control for individual heterogeneity. Such heterogeneity can be thought to consist of unobserved 'ability' when considering the determinants of hourly wages and individ-

If we estimate the wage equation using OLS and use the predicted values in the supply equation the fixed effects estimator of LNWAGE is 5.166. Comparing this estimator to the results of 2SLS again suggests a positive correlation between unobserved heterogeneity and wages re-enforcing the view that unobserved heterogeneity in the supply equation is likely to reflect, at least in part, unobserved ability and preferences.

[24] Strictly speaking the elasticities vary by individual but are presented here as calculated at the mean of hours of work.

ual preferences or constraints over the allocation of time when considering hours of labour supplied. The BHPS sample exploited consists of females who were observed in at least one wave to be employed as a nurse or midwife, or who held a nursing qualification irrespective of whether they were observed to have worked as a nurse during the sample period. To test for potential selection bias we employ variable addition panel data procedures proposed by Wooldridge (1995). The endogeneity of wages in the model of labour supply is accounted for by using 2-stage least squares.

Accounting for the endogeneity of wages has a profound effect on the estimates of the impact of hourly wages. Treating wages as exogenous results in negative elasticities of hours of labour supplied with respect to the logarithm of hourly wages. In contrast, the 2-stage least squares estimates are positive and highly significant. The elasticity implied by the estimate without controlling for unobserved individual heterogeneity or selection bias is 0.29. Once individual hetergeneity has been controlled for the estimate of the elasticity increases to 0.40. We do not find a significant effect of selection bias once we control for the endogeneity of wages. These estimates are small and imply only moderate increases in hours of labour supplied can be achieved through increases in wages. The results are in line with other studies of the labour response of UK nurses. Phillips (1995) reports an elasticity of 0.15 but this appears to relate to an elasticity of hours of work with respect to the logarithm of hourly wages and translates to an elasticity with respect to hourly wages of 0.25. Skåtun et al. (2002) report a corresponding elasticity of 0.34. The differences in the estimates may be due to different sample selection criteria used in the studies cited. Phillips focused attention on qualified and unqualified female nurses in the UK in 1980 while Skåtun et al. (2002) limited their study to qualified married or cohabiting female nurses and midwives. The sample used in this study consists of females who were observed in at least one wave to be employed as a nurse or midwife, or who held a nursing qualification. Other differences arise through the estimation techniques employed. While previous studies have relied on cross sectional data, we have been able to exploit the time dimension inherent in a panel survey to control for individual heterogeneity. Further, the richness of information contained in the BHPS allows us to condition on a wide range of confounding factors and obtain a useful instrument set to model the endogeneity of wages.

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Table 1: Variable definitions and sample means

| | | HOURS $NT = 962$ | WAGES $NT = 962$ | PARTICIPATION $NT = 2401$ |
|---|---|---|---|---|
| HRSWK | Usual weekly hours worked including overtime | 32.74 | - | - |
| LNWAGE | Log hourly wage | 2.01 | 2.01 | - |
| AGE | Age of respondent | 37.20 | 37.20 | 45.56 |
| CARERHH | 1 if care for other in household, 0 otherwise | .03 | - | .04 |
| HOSPHOME | 1 if work in hospital/nursing home, 0 otherwise | .73 | .73 | - |
| PRIVAGEN | 1 if work for private sector or an agency, 0 otherwise | .01 | .01 | - |
| MANSUP | 1 if manage/supervise other staff, 0 otherwise | .72 | .72 | - |
| NGHTWRK | 1 if work at night , 0 otherwise | .17 | .17 | - |
| VARWRK | 1 if times of work varies, 0 otherwise | .10 | .10 | - |
| ROTAWRK | 1 if rotate times of work, 0 otherwise | .38 | .38 | - |
| MARCOUP | 1 if married or living as a couple, 0 otherwise | .80 | .80 | .70 |
| NCH04 | Number of children in household aged 0 to 4 years | .19 | .19 | .14 |
| NCH511 | Number of children in household aged 5 to 11 years | .36 | .36 | .33 |
| NCH1218 | Number of children in household aged 12 to 18 years | .22 | .22 | .17 |
| MIDWIFE | 1 if respondent is a midwife, 0 if nurse | .07 | .07 | - |
| HHINC | Household yearly income excluding respondent's/1000 | 12.38 | 12.38 | 10.47 |
| NLBINC | Respondent's non-labour income | 87.01 | 87.01 | 205.11 |
| WHITE | 1 if ethnic status is white, 0 otherwise | .93 | .93 | .95 |
| DEGHDEG | 1 if degree or higher degree, 0 otherwise | - | .13 | .56 |
| HNDALEV | 1 if HND, HNCT or A level (or equivalent), 0 otherwise | - | .37 | .10 |
| OLEVCSE | 1 if O level or CSE (or equivalent), 0 otherwise | - | .40 | .29 |
| EXP | Duration of spell in current job in years | - | 4.53 | - |
| LEMPLOY | 1 if employed in year previous to interview, 0 otherwise | - | .91 | .56 |
| JBSIZE | Number employed at workplace | - | 510.21 | - |
| WKSEMP | Weeks employed in year of interview | - | 49.96 | - |
| CAREFREE | 1 if have childcare and it is provided free of charge, 0 otherwise | - | .13 | - |
| CAREPAID | 1 if have childcare and it is paid for, 0 otherwise | - | .12 | - |
| PARTRATE | Labour force participation rate in region of residence | - | .50 | .50 |
| PARTICN | 1 if participate in labour force as a nurse/midwife, 0 otherwise | - | - | .41 |

Table 2: Labour supply

| | OLS $N = 287$ $NT = 962$ | | FE $N = 160$ $NT = 835$ | | FE + SS $N = 160$ $NT = 835$ | | 2SLS $N = 287$ $NT = 962$ | | FE-2SLS $N = 160$ $NT = 835$ | | FE-2SLS + SS $N = 160$ $NT = 835$ | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| LNWAGE | -1.462 | (.804) | -4.449 | (.863) | -4.703 | (.862) | 9.438 | (1.982) | 13.023 | (4.140) | 12.329 | (4.284) |
| AGE | .278 | (.238) | .931 | (.355) | .774 | (.356) | -.703 | (.305) | -1.565 | (.728) | -1.536 | (.720) |
| AGESQRD | -.559 | (.296) | -.910 | (.438) | -.660 | (.444) | .606 | (.376) | 1.186 | (.736) | 1.205 | (.721) |
| CARERHH | -3.411 | (1.543) | -1.250 | (1.600) | -1.471 | (1.591) | -4.392 | (1.695) | -1.884 | (2.046) | -1.943 | (2.016) |
| HOSPHOME | -.770 | (.703) | .317 | (.680) | .223 | (.677) | .460 | (.795) | 1.858 | (.937) | 1.771 | (.935) |
| PRIVAGEN | -3.209 | (2.317) | -2.777 | (2.028) | -2.746 | (2.015) | -1.317 | (2.553) | 2.456 | (2.850) | 2.288 | (2.828) |
| MANSUP | .846 | (.634) | 1.733 | (.535) | 1.717 | (.532) | -1.231 | (.772) | -.056 | (.796) | .0004 | (.792) |
| NGHTWRK | -4.442 | (.867) | -2.555 | (.930) | -2.654 | (.925) | -3.886 | (.953) | -2.599 | (1.187) | -2.633 | (1.170) |
| VARWRK | -.379 | (.981) | -1.576 | (.882) | -1.682 | (.877) | .478 | (1.082) | -1.068 | (1.132) | -1.124 | (1.118) |
| ROTAWRK | 1.266 | (.729) | 1.030 | (.705) | 1.004 | (.701) | 1.927 | (.804) | .822 | (.901) | .820 | (.888) |
| MARCOUP | -1.340 | (.756) | -1.988 | (1.020) | -2.222 | (1.017) | -1.471 | (.828) | -2.357 | (1.304) | -2.429 | (1.287) |
| NCH04 | -5.877 | (.616) | -4.861 | (.533) | -4.877 | (.530) | -6.177 | (.676) | -4.351 | (.690) | -4.374 | (.681) |
| NCH511 | -3.053 | (.448) | -2.465 | (.535) | -2.378 | (.533) | -2.037 | (.517) | -1.402 | (.725) | -1.407 | (.714) |
| NCH1218 | -2.380 | (.548) | -.364 | (.569) | -.393 | (.565) | -1.996 | (.602) | .541 | (.755) | .500 | (.747) |
| MIDWIFE | -1.159 | (1.029) | -.589 | (1.701) | -.678 | (1.690) | -2.376 | (1.142) | -1.589 | (2.182) | -1.587 | (2.149) |
| HHINC | -.081 | (.023) | .027 | (.028) | .016 | (.028) | -.097 | (.025) | .016 | (.036) | .013 | (.035) |
| NLBINC | -.0033 | (.0013) | -.0025 | (.00096) | -.0027 | (.00096) | -.0037 | (.0015) | -.0020 | (.0012) | -.0021 | (.0012) |
| WHITE | -3.577 | (1.096) | - | - | - | - | -5.035 | (1.223) | - | - | - | - |
| SCOT | 2.584 | (1.340) | 7.880 | (6.671) | 2.434 | (5.096) | 1.805 | (1.472) | 5.847 | (4.754) | 7.785 | (6.575) |
| WALES | 3.752 | (1.454) | 2.820 | (6.804) | 2.130 | (6.766) | 3.565 | (1.591) | 4.277 | (8.688) | 3.976 | (8.569) |
| NIRELAND | 2.146 | (2.403) | - | - | - | - | 1.965 | (2.629) | - | - | - | - |
| NORTHE | 1.194 | (1.376) | - | - | - | - | 1.285 | (1.506) | - | - | - | - |
| NORTHW | 4.989 | (1.478) | 4.185 | (6.238) | 5.030 | (6.206) | 6.073 | (1.627) | 8.691 | (8.026) | 8.842 | (7.904) |
| LONDON | .908 | (1.503) | 1.021 | (3.792) | 1.017 | (3.769) | -1.072 | (1.675) | 3.764 | (4.879) | 3.668 | (4.810) |
| MIDLAND | 1.341 | (1.391) | 4.782 | (4.403) | 4.558 | (4.377) | 1.333 | (1.522) | 6.298 | (5.629) | 6.165 | (5.549) |
| SOUTHE | 2.735 | (1.353) | -.961 | (3.505) | -.387 | (3.489) | 2.384 | (1.481) | 2.033 | (4.525) | 2.138 | (4.455) |
| INVMILLS | - | - | - | - | -2.303 | (.762) | - | - | - | - | -.836 | (1.028) |
| ELASTICITY OF HOURS W.R.T. WAGES | -.045 | (.025) | -.136 | (.026) | -.144 | (.026) | .288 | (.061) | .398 | (.126) | .377 | (.131) |

1. Sargan test of over-identifying restrictions: 2SLS: $\chi^2_{17} = 22.018, p = 0.184$: FE-2SLS: $\chi^2_{13} = 15.850, p = 0.257$: FE-2SLS + SS: $\chi^2_{13} = 16.092, p = 0.244$.
2. WHITE, SCOT, NIRELAND, NORTHE dropped in fixed effects models due to lack of within individual variation.
3. Standard errors are given in parentheses.

Table 3: Wage equation

| | 2SLS $NT = 962$ | | FE-2SLS $NT = 835$ | | FE-2SLS + SS $NT = 835$ | |
|---|---|---|---|---|---|---|
| AGE | .081 | (.009) | .159 | (.015) | .156 | (.016) |
| AGESQRD | -.096 | (.011) | -.135 | (.019) | -.130 | (.020) |
| CARERHH | .103 | (.058) | .046 | (.072) | .042 | (.072) |
| HOSPHOME | -.135 | (.027) | -.106 | (.031) | -.106 | (.031) |
| PRIVAGEN | -.191 | (.088) | -.319 | (.090) | -.317 | (.090) |
| MANSUP | .160 | (.023) | .101 | (.024) | .101 | (.024) |
| NGHTWRK | .003 | (.033) | .009 | (.042) | .004 | (.042) |
| VARWRK | -.066 | (.036) | -.025 | (.039) | -.028 | (.040) |
| ROTAWRK | -.057 | (.028) | .018 | (.032) | .017 | (.032) |
| MARCOUP | .017 | (.028) | .008 | (.045) | .002 | (.045) |
| NCH04 | -.007 | (.028) | .018 | (.028) | .016 | (.028) |
| NCH511 | -.076 | (.018) | -.044 | (.024) | -.042 | (.024) |
| NCH1218 | -.034 | (.021) | -.038 | (.026) | -.039 | (.026) |
| MIDWIFE | .057 | (.038) | .078 | (.076) | .076 | (.076) |
| HHINC | .0009 | (.0009) | .0001 | (.001) | -.0002 | (.001) |
| NLBINC | .000009 | (.00005) | -.00003 | (.00004) | -.00003 | (.00004) |
| WHITE | .143 | (.043) | - | - | - | - |
| SCOT | .033 | (.051) | -.264 | (.229) | -.245 | (.230) |
| WALES | .038 | (.059) | .00002 | (.304) | -.011 | (.304) |
| NIRELAND | -.086 | (.090) | - | - | - | - |
| NORTHE | .025 | (.052) | - | - | - | - |
| NORTHW | -.038 | (.056) | -.218 | (.280) | -.177 | (.281) |
| LONDON | .157 | (.059) | -.192 | (.169) | -.185 | (.169) |
| MIDLAND | .002 | (.052) | -.067 | (.198) | -.061 | (.198) |
| SOUTHE | -.003 | (.054) | -.186 | (.156) | -.169 | (.157) |
| DEGHDEG | .347 | (.044) | - | - | - | - |
| HNDALEV | .265 | (.041) | - | - | - | - |
| OCSE | .200 | (.038) | - | - | - | - |
| EXP | .013 | (.005) | -.005 | (.005) | -.006 | (.005) |
| EXPSQRD | -.009 | (.019) | .034 | (.022) | .036 | (.022) |
| JBSIZE | .00008 | (.00003) | .00003 | (.00003) | .00003 | (.00003) |
| WKSEMP | .003 | (.001) | .003 | (.001) | .002 | (.001) |
| CAREFREE | -.016 | (.035) | -.124 | (.039) | -.125 | (.039) |
| CAREPAID | .089 | (.039) | -.101 | (.040) | -.101 | (.040) |
| PARTRATE | .964 | (.360) | 1.472 | (.415) | 1.468 | (.414) |
| INVMILLS | - | - | - | - | -.052 | (.037) |

1. WHITE, SCOT, NIRELAND, NORTHE, DEGHDEG, HNDALEV, OCSE dropped in fixed effects models due to lack of within individual variation.
2. Standard errors are given in parentheses.
3. Time dummies suppressed from results.