The impact of health on wages: Evidence from the British Household Panel Survey

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Abstract

While income has been shown to positively affect health, little evidence has been offered for the impact of health on wage rates, particularly for developed economies. Evidence is meagre for the U.K. This paper considers the effect of self-assessed general and psychological health on hourly wages using longitudinal data from the six waves of the British Household Panel Survey. We employ single equation fixed effects and random effects instrumental variable estimators suggested by Hausman and Taylor(1981), Amemiya and MaCurdy(1986), and Breusch, Schmidt and Mizon(1989). Our results show that reduced psychological health reduces the hourly wage for males, while excellent self-assessed health increases the hourly wage for females. We also confirm the findings of previous work which suggested that the majority of the efficiency gains from the use of the instrumental variables estimators fall on the time-invariant endogenous variables, in our case academic attainment, and add further support to the hypothesis of a negative correlation between educational attainment and individual characteristics which affect wages.
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1 Introduction

Evidence suggesting the existence of causal effects of income and wages on health has been accruing recently(e.g. Ettner(1996)). However, while previous work has recognized that income affects health, and has estimated models which account for potential endogeneity, there is little evidence concerning the impact of health on wages, particularly for developed economies. Virtually no evidence exists using recent UK data. This paper addresses this issue.

There are a number of reasons that health may impact on wages in a developed economy. Firstly, as noted by Mushkin(1962), Grossman and Benham(1974), Luft(1975) and Berkowitz *et al.*(1983), an increase in health leads to an increase in productivity, which should be reflected in an increased wage rate. Secondly, an employer may perceive health to be correlated with unobservable attributes which affect productivity and hence offer higher wages to healthier individuals. Thirdly, an individual may be discriminated against because they are unhealthy, irrespective of their productivity. While we do not attempt to distinguish between dicrimination and productivity effects, we abstract from reason two by using instrumental variable techniques. In doing so, we also obtain an indication of the portion of the conditional healthy-unhealthy wage differential which is due to correlated and unobserved factors.

Existing literature has in general found a positive impact of healthiness on wages and/or income. However, the vast majority of work in this area uses cross-sectional data and various forms of instrumental variable techniques.[1] These techniques require finding valid instruments which are uncorrelated with the error term and predict well the endogenous variables for each equation estimated. As noted by Haveman *et al.*(1994), this becomes more problematic as the number of equations increases.

We use panel data and instrumental variable estimators which are capable of overcoming the problems of endogeneity, which causes the usual GLS estimator to be biased and inconsistent, and the inefficiency of fixed effects or within group estimators(Baltagi(1995)). Further, these estimators have the advantage over the usual within groups estimator of allowing time invariant effects such as ethnicity and educational status to be included. In particular, we follow the approach of using within-model instruments originally suggested by Hausman and Taylor(1981), and augmented by Amemiya and MaCurdy(1985) and Breusch, Schmidt and Mizon(1989). This methodology circumvents the problem of finding valid and relevant outside instruments that plagues many cross-sectional studies. These estimators require increasingly strong exogeneity assumptions to ensure consistency, but have the potential for increased efficiency. We exploit the overidentification restrictions implied by our empirical model to explicitly test the exogeneity assumptions. Applications of these techniques to wage equations are the original contribution by Hausman and Taylor(1981), and a comparison of the estimators implemented by Cornwell and Rupert(1988), and Baltagi and Khanti-Akom(1990). However, health has, in general, been assumed exogenous in panel data models of wages,(Hausman and Taylor(1981)), or it has been excluded from the model(Cornwell and Rupert(1988), Baltagi and Khanti- Akom(1990), Kim and Polachek(1993)). Here, we assume that health, while not simultaneously determined, is

[1] The exception to this rule is Haveman *et al.*(1994). However, their use of longitudinal data is to increase the sample size and to enable a measure of lagged health to be employed. They do not exploit the longitudinal nature of the dataset in attempting to overcome issues of endogeneity, and do not impose the implied restrictions on the covariance structure offered by models including individual effects.

endogenous in a model of wages. This assumes that health is correlated with the individual specific and time invariant component of wages, but not with the period and individual specific error which determines wages.

While health may affect wages, it is also probable that wages impact on health. For example, if wages exert a positive effect on labour supply, as suggested by Grossman and Benham(1974) amongst others, and income positively affects health, the *OLS* estimator of the impact of health on wages will be upward biased. There may also be a period of transition during which wages respond to health. Our use of panel data and health indicators which allow for this time lag may capture better the impact of health on wages than using contemporaneous measures, while also dealing with the issue of endogeneity. We also obtain results which assume greater time lags and compare the magnitudes of the responses.

In estimating the model we exploit the panel data available in the British Household Panel Survey(BHPS). This currently consists of six waves and includes rich information on occupational, socio-demographic and health variables. Although the BHPS has been used to estimate models of wages and earnings, (e.g. Harkness(1996), Disney and Gosling(1998), Hildreth(1999), Walker and Thompson(1996)), these models ,with the exception of Walker and Thompson(1996), have not included a measure of health among the regressors.

The outline of the paper is as follows. In section 2, we review previous work which has attempted to estimate the impact of health on wages in developed countries. Section 3 outlines our empirical model and estimation strategy. In section 4, we describe the BHPS dataset, while section 5 presents our results. Section 6 provides a short conclusion.

2 Previous work

Berkowitz *et al.*(1983) examine a model where health capital influences productivity as well as labour supply.[2] Using US data on white males from the survey of disabled and non-disabled adults and eight dichotomous indicators of impairments, they find that six indicators have a negative effect on wages using *GLS*.

Lee(1982) estimates a general simultaneous equations model with multiple discrete indicators for unobserved health capital, generalizing the dummy variables simultaneous system of Heckman(1978). Using US data from the National Longitudinal Survey of Men for 1966, he finds that unobserved health capital has a positive impact on wages both before and after accounting for endogeneity, with the coefficient 25% lower after accounting for the potential impact of wages on health. Lee's estimates also indicate a potential bias in estimates of the return to schooling when health is considered exogenous.

Haveman *et al.*(1994) estimate a simultaneous equations model for work-hours, wages, and health, using GMM to account for simultaneity and to allow weak restrictions on the covariance-

[2]The original model of Grossman(1972) classified individuals as either healthy or unhealthy, ignoring the conceptually continuous status of pathological diversity. This led him to treat wages as invariant to health, while work-time was considered endogenous. However, Grossman and Benham(1974) allow the wage rate to be endogenously determined. Haveman *et al.*(1994) also note that wages play an important role in the investment version of the Grossman model but are assumed exogenous. In particular an increase in wages leads to an increase in the marginal return to health investment and an increase in optimal health. They also note that in other formulations of the Grossman model the impact of wages on health is ambiguous.

structure of the model. Using longitudinal data on 613 white males observed over 8 years from the US Panel Study of Income Dynamics, they find lagged ill-health(measured by a dichotomous indicator of work-limitations) to reduce wages and find a *larger* effect after accounting for endogeneity. This qualitative result was also found by Grossman and Benham(1974) using two-stage least squares.[3]

Sundberg(1996) estimates a three equation simultaneous equations model of health, work hours and wages using Swedish data from 1991. She uses a self-assessed health variable and converts it into a continuous variable assuming a standard log-normal distribution for the latent index characterizing health. Using 3SLS Sundberg(1996) finds qualitatively similar results to Haveman *et al.*(1994), at least for men. For women the impact of self-assessed health on wages is insignificant.

Using the first three waves of the BHPS, Walker and Thompson(1996) estimated a model of hourly wages which included measures of disability. Applying both OLS and a selectivity corrected wage equation they found disability to reduce years of schooling, wages and the probability of labour force participation. They found disability to mainly affect participation rather than wages, and that once the endogeneity of schooling had been accounted for the effect of disability on wages was very small.

Madden(1999) uses cross-sectional data on 8747 couples from the U.K. 1995 Family Resources Survey, and attempts to decompose the healthy-unhealthy wage differential into productivity and discrimination components. He finds that health status is endogenous in wage equations for males and females, and that having taken into account the direct effect of health status on productivity, discrimination is, in general, an insignificant component of the observed mean wage differential. This may allow us to conclude that, having accounted for endogeneity, the coefficients we obtain are reflective of productivity differentials rather than discrimination.

3 Empirical Model and Estimation Methods

We adopt a typical specification of the wage function derived from the theoretical investigations of Mincer(1974). Mincer showed that the natural logarithm of annual earnings or the natural log of the wage rate should be positively related to investment in formal schooling and to investment in on-the-job training. We modify the empirical relationship to account for the impact of health, the panel nature of the data and the effect of other variables. Following the notation of Hausman and Taylor(1981)(hereafter HT),

$$W_{it} = X_{it}\beta + Z_i\gamma + \alpha_i + \eta_{it}, \quad i = 1, 2..., N, \ t = 1, 2, ..., T \tag{1}$$

where i indexes individuals and t indexes time periods. W_{it} is the logarithm of hourly wages, and X_{it} is a $K \times 1$ vector of time varying regressors including age, work experience and health. Z_i is a $G \times 1$ vector of time invariant regressors including qualifications and ethnicity. α_i is an individual specific and time invariant error component, assumed iid $N(0, \sigma_\alpha^2)$, and η_{it} is a classical mean zero disturbance, iid $N(0, \sigma_\eta^2)$. β and γ are conformable vectors of parameters associated with the regressors. Observations are ordered first by individual and then by time, so

[3] Luft(1975), Grossman and Benham(1974), and Bartel and Taubman(1979) also find that healthiness increases wages.

that α_i and each column of Z_i are NT vectors having blocks of T identical entries within each $i = 1, ..., N$. We assume that the η_{it} are uncorrelated with both the explanatory variables and the effects α_i. The effects α_i may be correlated with parts of X and Z.

Our estimation strategy is as follows. We first estimate the model by OLS. If the errors are uncorrelated with the regressors than OLS is unbiased and consistent. However, it will be inefficient as the errors are correlated within individuals. Secondly we estimate the within regression. The within-group estimator is unbiased and consistent as N and/or $T \to \infty$ even if α_i is correlated with the regressors. Thirdly, we implement the GLS estimator which is a matrix weighted average of the between group and within group estimators. GLS will be efficient if the errors are uncorrelated with the regressors, but will be inconsistent as $N \to \infty$ for fixed T if the regressors are correlated with either the individual-specific component α_i or the idiosyncratic component η_{it}. We then implement three instrumental variables estimators suggested by HT, AM and BMS, which, while requiring increasingly strong exogeneity asumptions, are increasingly precise.

Define $P_V = [I_N \otimes (1/T)\iota_T \iota_T']$ where ι_T is a $T \times 1$ vector of ones and $\otimes$ denotes the Kronecker product operator. With data grouped by individuals, P_V transforms a vector of observations into a vector of group means. Define also $Q_V = I_{NT} - P_V$. Q_V produces a vector of deviations from group means. Q_V is orthogonal by construction to any time-invariant vector of observations. To obtain the within groups estimator, multiply (1) by Q_V to obtain,

$$Q_V W_{it} = Q_V X_{it}\beta + Q_V \eta_{it} \tag{2}$$

as $Q_V Z_i \gamma = Q_V \alpha_i = 0$. Ordinary least squares estimation of β in equation (2) defines the within groups estimator as :

$$\hat{\beta_W} = (X_{it}' Q_V X_{it})^{-1} X_{it}' Q_V W_{it} \tag{3}$$

To obtain the between groups estimator multiply (1) by P_V to obtain

$$W_{i\bullet} = X_{i\bullet}\beta + Z_i\gamma + \alpha_i + \eta_{i\bullet} \tag{4}$$

with a $(\bullet)$ subscript indicating a within group average. The between groups estimator is obtained by ordinary least squares estimation of (4)(denoted $\hat{\beta_B}$ and $\hat{\gamma_B}$), and because of the presence of α_i, both $\hat{\beta_B}$ and $\hat{\gamma_B}$ are biased and inconsistent if α_i is correlated with the regressors. In the absence of correlation between the error components and the regressors, $cov(\epsilon_{it}|X_{it}, Z_i) = 0$, the optimal use of within and between group information defines the GLS estimator. From equation (1), $cov(\epsilon_{it}|X_{it}, Z_i) \equiv \Omega = \sigma_\eta^2 I_{NT} + \sigma_\alpha^2[I_N \otimes \iota_T\iota_T']$ where $\epsilon_{it} = \alpha_i + \eta_{it}$. Equation (1) can then be viewed as a linear regression with a non-scalar disturbance covariance matrix. Hausman and Taylor show(p1381) that transforming equation (1) by the $NT \times NT$ non-singular matrix $\Omega^{-1/2}$ leads to a scalar covariance matrix and an equation in matrix notation:

$$\Omega^{-1/2}W = \Omega^{-1/2}X\beta + \Omega^{-1/2}Z\gamma + \Omega^{-1/2}(V\alpha + \eta) \tag{5}$$

where $\Omega^{-1/2} = Q_V + \theta P_V$ and $\theta^2 = (\sigma_\eta^2 + T\sigma_\alpha^2)^{-1}\sigma_\eta^2$. Performing OLS on (5) leads to the GLS estimator for β and analogously for γ.

$$\hat{\beta_{GLS}} = \pi\hat{\beta_B} + (1-\pi)\hat{\beta_W} \tag{6}$$

where π and $1-\pi$ are inversely proportional to the inverses of the covariance matrices of the between and within estimators respectively. As noted above, the feasible[4] GLS estimator will be biased and inconsistent for β and γ if the individual effects are correlated with the regressors as it combines the biased and inconsistent between estimator and the unbiased and consistent within estimator. It should also be noted that the within estimator by construction is unable to estimate the parameters of the time-invariant variables Z_i. HT, as a precursor to the presentation of their instrumental variables estimator, show that these parameters may be consistently recovered using an auxiliary regression even when the α_i's are correlated with the columns of Z_i. The use of this estimator also allows construction of consistent estimators of the variance components. However, the within estimator is not efficient for either the time-varying or time-invariant parameters. As an indication of the utility of the HT estimator we use a Hausman test(Hausman(1978)) to compare the within and GLS estimates. Under the null of correct specification(exogeneity), the within estimates should be close to the GLS results for the time varying regressors. The test statistic is constructed as $M = q'cov(q)^{-1}q$ where $q = \hat{\beta_W} - \hat{\beta_{GLS}}$ and $cov(q) = cov\hat{\beta_W} - cov\hat{\beta_{GLS}}$. M is asymptotically distributed under H_0 as χ^2_K. Significant differences between the two vectors suggest mis-specification and the utilization of within groups or instrumental variable techniques to overcome endogeneity. However, as noted above, , the Hausman test compares only the coefficients of the time-varying regressors. Hence, the employment of the instrumental variables estimators may remain productive even if the null of exogeneity is not rejected. HT propose an instrumental variables estimator which is at least as efficient as the within estimator and avoids the inconsistency of the GLS estimator. Following Cornwell and Rupert(1988) and noting the stacking of the NT observations over individuals and time, with the faster index over time, we can write (1) as :

$$W = X\beta + Z\gamma + V\alpha + \eta \tag{7}$$

where W and η are $NT \times 1$, X is $NT \times K$, and Z is $NT \times G$, and V is a matrix of individual specific dummy variables). For any matrix A we define the $P_A = A(A'A)^{-1}A'$ as the projection onto the column space of A. The projection onto the null space of A is $Q_A = I_{NT} - P_A$ where I is the identity matrix of order NT. Following HT partition X and Z into $X = (X_1, X_2)$ and $Z = (Z_1, Z_2)$, and assume that X_2 and Z_2 are correlated with the effects α, while X_1 and Z_1 are not. X_1 has k_1 columns, X_2 has k_2 columns, and $k_1 + k_2 = K$; Z_1 has g_1 columns and Z_2 has g_2 columns, with $g_1 + g_2 = G$. Transforming (7) to have a scalar covariance matrix as suggested above for the GLS estimator gives (5). Then with an instrument set A based on the regressors, IV is performed on (5). HT use the instrument set:

$$A_1 = (Q_V X_1, Q_V X_2, P_V X_1, Z_1) \tag{8}$$

[4]Implementation of the GLS estimator requires estimates of the variance components. While a consistent estimator of σ^2_η can be obtained from the residuals of the within regression when α is correlated with the regressors, the estimator of Ω will be biased and inconsistent if α_i is correlated with the regressors as it uses the sum of squared residuals from the biased and inconsistent between regression. Our results for the GLS estimator are based on the auxiliary regression suggested by HT.

The k_1 exogenous columns of X_1 included in the model provide the identification conditions for Z_2. While the parameters β_1 are identified by the deviations from means $Q_V X_1$, and the parameters of the time varying endogenous parameters are identified by the deviations from means $Q_V X_2$, and the parameters γ_1 are identified from their actual values, the mean values $P_V X_1$ provide sufficient information for the identification of the parameters of the time-invariant endogenous variables Z_2. Hence the order condition for the HT estimator to be identified is that $k_1 \geq g_2$.

While the HT estimator is both consistent and more efficient than the within estimator if the model is overidentified and the partition of the variables into exogenous and endogenous components is correct, it is inconsistent if some of the assumed exogenous variables are correlated with α_i. We can test for this using a Hausman test comparing the results of the within estimator with the HT estimator. Under the null that the overidentification conditions are valid, a test statistic analogous to M above is, in general, asymptotically distributed as $\chi^2_{k_1-g_2}$.[5] Conditional on the validity of the instrument set of HT, it is possible to obtain a potentially more efficient estimator, as suggested by Amemiya and MaCurdy(1986)(hereafter AM). Again following Cornwell and Rupert(1988), let X_1^* be an $NT \times TK$ matrix where each column contains values of X_{1it} for a single time period. For example, the tth column of $X_{1t}^* = (X_{11t}, ..., X_{11t}, ..., X_{1Nt}, ..., X_{1Nt})$ for each $k \in K$. The AM estimator is IV on (5) using the set of instruments :

$$A_2 = (Q_V X_1, Q_V X_2, X_1^*, Z_1) \tag{9}$$

While HT use each X_1 variable as two instruments, AM use each of these variables as $(T+1)$ instruments. Following the same reasoning as used to ascertain the conditions for existence of the HT estimator it can be seen that the order condition for the AM estimator is that $Tk_1 \geq g_2$. Although the AM estimator, if consistent, is no less efficient than the HT estimator, consistency requires a stronger exogeneity assumption. As noted by Cornwell and Rupert(1988), HT only requires the means of the X_1 variables to be uncorrelated with the effects while the AM estimator requires uncorrelatedness at each point in time. The extra instruments add explanatory power to the reduced form model for Z_2 if there is variation over time in the correlation of X_1 and Z_2. Again using a Hausman test, we are able to test the extra exogeneity assumptions by comparing the HT and AM estimators.

Breusch, Mizon and Schmidt(1989) derive a potentially more efficient AM-like estimator by noting that the AM instrument set can be redefined as:

$$A_2 = (Q_V X_1, Q_V X_2, P_V X_1, (Q_V X_1)^*, Z_1) \tag{10}$$

where $Q_V X_1$ is defined in the same way as X_1^*, and noting that T columns must be excluded from the set $(Q_V X_1)^*$ due to the fact that for each variable only $T-1$ deviations from means are linearly independent. BMS then extend this treatment of the X_1 variables to the X_2 variables using the instrument set:

[5] It should be noted that although the number of degrees of freedom of the distribution is equal to the number of *overidentifying* restrictions, all of the exogeneity information assumed is subject to test using this procedure as the alternative does not require any of the columns of X or Z to be uncorrelated with α(HT(p1389)). It should also be noted that in the case where $k_1 = g_2$, the within estimator and the HT estimator are numerically identical.

$$A_3 = (Q_V X_1, Q_V X_2, P_V X_1, (Q_V X_1)^*, (Q_V X_2)^*, Z_1), \quad (11)$$

with $(Q_V X_2)^*$ defined as $(Q_V X_1)^*$. So, again noting the necessity of dropping T columns, and using similar reasoning to that used above, the BMS order condition is that $Tk_1 + (T-1)k_2 \geq g_2$. The potential efficency gain depends on whether the extra instruments are both valid and relevant. If the variables in X_2 are correlated with the effects only through a time-invariant component the additional BMS instruments are valid; it is only possible for the extra instruments to be invalid if the correlation with the individual effects is time varying. On the other hand, for the extra instruments to add explanatory power in a reduced from for Z_2 requires the correlation of X_2 with Z_2 to be time-varying. Otherwise, they add nothing over $(Q_V X_2)$. Again, the overidentification assumptions are testable using a Hausman test to compare the BMS and AM estimators.

Here we assume that health, while not simultaneous, is endogenous in a model of wages. As noted above, this assumes that health is correlated with the individual specific and time invariant component of wages, but not with the period and individual specific error which determines wages. The validity of our approach is dependent on the hypothesis that any serial correlation in the error term of the wage equation is due to the individual specific component. If there is serial correlation in the period and individual specific error and wages affect health contemporaneously as found (for males) by Sundberg(1996), then past health will be correlated with the error in the current period, rendering the model 'simultaneous' and the approaches suggested above invalid. Alternatively, if current health is employed, and wages impact on health contemporaneously, the model immediately becomes simultaneous, and the approaches above are again invalid. Further, if wages affect health with a lag, current and past health will remain endogenous and the approaches below valid, but 'simultaneity' will be introduced if there is serial correlation in the period and individual specific error which determines wages.

4 Dataset

In estimating the model we exploit the panel data available in the British Household Panel Study(BHPS), consisting of six waves and including rich information on occupational, socio-demographic and health variables. The BHPS is a longitudinal survey of private households in Great Britain(England, Wales, and Scotland), and was 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 1st September and 30th April 1991.[6] The same individuals are re-interviewed in successive waves and, if they split off 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 of Britain. Following the collection of household level information, individual questionnaires are administered which cover questions on neighbourhood, demographics, residential mobility, health and caring, current employment and

[6] The initial selection of households for inclusion in the survey was performed using a two-stage stratified systematic sampling procedure designed to give each address an approximately equal probability of selection. For further details see Taylor(1997).

earnings, employment changes over the past year, values and opinions, and household finance. Individuals were also asked to complete a self-completion questionnaire which included questions where answers may be particularly vulnerable to the presence of others.

The sample for waves two to six consists of all eligible adults in all households where there is at least one interview at wave one.[7] For ease of estimation, we use a subset of the original sample members who completed the questionnaire at all six waves, and who gave valid responses for the variables we utilise in our estimation.[8] After excluding individuals with missing values on variables of interest and who had not completed their formal education, we obtained a working sample of 1670 individuals, consisting of 859 males and 811 females. In particular, and most importantly, we restrict our population of interest to those who were in employment in each of the six waves, with our sample restricted to those who gave responses from which we were able to construct an average hourly wage. Hence we attempt to abstract from issues of labour supply, and confine our analysis to the impact of health status on labour productivity, as proxied by average hourly wages. This is of course likely to underestimate the full effect of health status on *expected* wages, as those individuals who leave the labour force are likely to be those with worst health.[9] Others, notably Grossman and Benham(1974), Haveman *et al*(1994) and Sundberg(1996) have estimated models where labour supply, wages, and health are determined interdependently. They generally find good health to have a positive effect on labour supply. We also define a balanced sub-sample consisting of individuals who were fully employed in each time period(those who worked more than 30 hours per week). The fully employed sample includes 1296 individuals, of which 838 are male and 458 female. The use of this alternative sample allows us to obtain an indication of the impact of health variation which is due to changes in labour supply. For the health and other variables, the fully employed sample restricts wage variation to job type and/or productivity change. The utilisation of the full-sample including part-time and full-time observations allows individuals to respond to a reduction in health by reducing labour supply. This may lead to an additional or compensating hourly wage reduction/ increase which will be indicated indirectly by a larger/smaller impact of health variation for this sample relative to the fully-employed sub-sample.[10]

[7] At wave one, there was at least one interview in 74% of eligible households, with full interviews with all eligible members in 65% of households. 92% of eligible individuals (households with at least one interview) responded with a full interview, with 2% of eligible individuals refusing to participate. At each wave between 5 and 7 % of individuals who responded with a full interview at the first wave refused to participate. Overall, 57% of those who responded with a full interview at wave one responded fully at every successive wave.

[8] Kim and Polachek(1993) find little difference between results obtained using an unbalanced and balanced sample in their analysis of male and female earnings functions, while Thomas and Strauss(1997) find no evidence of selection into market employment, when including a full specification of health indicators and determinants, on the wages of men and women in urban Brazil.

[9] An advantage with our approach is the avoidance of one cause of systematic measurement error in health; that associated with the conditional receipt of sickness benefit, or other forms of income support. This problem has been discussed by Kerkhofs and Lindeboom(1995).

[10] To ascertain this impact it would be preferable to estimate a model for part-time workers as performed by Harkness(1996). An alternative is to include a binary variable for part-time work using the full sample. This approach introduces simultaneity, and as found by Harkness(1996), a binary variable is unlikely to adequately capture the impact of part-time work, with stratification being the more appropriate strategy. However, this option is unavailable in our case as few individuals were found to be part-time workers in every wave for which we require wage rates.

Dependent variable

As there is no pre-constructed hourly wage variable in the BHPS we constructed an hourly wage variable as follows. Firstly, we divided usual gross monthly pay (including overtime) derived from the main job of an individual by the number of hours worked per month in their main job(including overtime).[11]We obtain the hourly wage in secondary jobs analogously and constructed an overall average wage by taking a weighted average of the hourly wage in the main and secondary jobs with weights equal to the proportions of total working time spent in their main and secondary jobs. Using this procedure we obtain a measure of 'maximum average' productivity; those individuals with relatively low wages are more likely to supplement their income with another job, which may be more highly paid, while those who receive relatively high average wages in their main job should be, *ceteris paribus*, less likely to seek a second job. This possibility seems to be borne out in our samples as the constructed average wage variable has a greater mean than the hourly wage from main job variable, while the hourly wage from secondary jobs variable has a lower mean than both.[12]

Before describing the regressors used in our analysis, it is useful to refer to equation (7). As noted above, X and Z can be separated into exogenous and endogenous components. Specifically, we partitioned X and Z into $X = (X_1, X_2)$ and $Z = (Z_1, Z_2)$, and assumed that X_2 and Z_2 are correlated with the effects α, while X_1 and Z_1 are not.

Time-varying Variables

Firstly, we describe our health variables which are time-varying and, we hypothesize, endogenous. We use a self-assessed health question which asks the individual to rate their health on average over the last twelve months relative to someone of their own age. This variable is coded as excellent, good, fair, poor, and very poor. We created three dummy variables equal to one if an individual has excellent health, has good health, or has fair health or worse. It is expected that the coefficients on the excellent and good health variables will be positive with a larger coefficient

[11]Approximately 5% of the full and fully-employed samples had their responses to the gross monthly pay variable imputed at each wave. 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. 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.

[12]Although we attempt to abstract from issues of labour supply in our analysis, we are unable to do so wholly. If individuals are paid overtime premia, then those individuals who commit to overtime work will, using our construction, be observed to receive a greater average 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. A similar perspective can be taken on the usage of the weighted average method to construct a 'maximum average' productivity measure.

on the excellent dummy.[13] The self-completion questionnaire described above also contains a reduced version of the General Health Questionnaire (GHQ) which was originally developed as a screening instrument for psychiatric illness but is often used as an indicator of subjective well-being. We use a composite measure derived from the results of this questionnaire which is increasing in ill-health. We expect the coefficient on this variable to be negative.[14] Given the possibility of a period of transition before health affects wages and the way in which our health and wage variables are measured, our preferred specification includes the current survey period values of GHQ and the current survey period values of self-assessed health.

Following Hildreth(1999) we use two variables to account for the effect of union status. The first is a binary variable which equals one if the individual has a recognised workplace union which covers pay and conditions negotiation for the type of job in which the individual is employed, and the individual is not a member of this union, and zero otherwise. The second union variable takes a value one if an individual is a member of this union and zero otherwise. Using the BHPS and the covered member dummy(COVMEM), and the covered non-member dummy(COVNON), Hildreth(1999) finds that the impact of unionisation is positive, with a larger effect for members than non-members. He observes negative selection effects for females for both forms of unionisation, indicating that those who join unions or are in establishments covered by union bargaining are using union status to compensate for their unobserved characteristics and maintain their wage. For males, these effects are positive in the production sector and small and negative across the whole sample. However, given that measurement error is exaggerated in a fixed effects model and leads the estimator to be biased towards zero for modest amounts of measurement error(see Freeman(1984)), the selection effect may be understated and could be large and negative for males(Hildreth(1999)). We also include a dummy variable which indicates whether an individual has undertaken any training or education related to their current employment. Given the expectation that training will not immediately impact on wages we include the lagged value of this variable(LJTRAIN). We hypothesize that this variable will have a positive coefficient.

We allow for a quadratic function of age and experience by including both the levels of these variables and their squares(AGE, AGESQRD,EXP,EXPSQRD). Age should capture general labour market experience and tenure effects. 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 concave function in experience. Similarly, we expect a concave function in age.

[13]Recoding was performed as the categories very poor and poor contained (in total) less than 4% of the observations in each of our samples.

[14]The twelve individual elements of the shortened GHQ are: concentration, sleep loss due to worry, perception of role, capability in decision making, whether constantly under strain, perception of problems in overcoming difficulties, enjoyment of day-to-day activities, ability to face problems, loss of confidence, self-worth, general happiness, and whether suffering depression or unhappiness. The respondent is asked to indicate on a four point ordinal scale how they have *recently* felt with respect to the item in question. The Likert scale which we employ obtains an overall score by summing the responses to each question, attaching values of zero to the best state and three to the worst.

Noting that the wage equation relates the *real* wage to human capital and other variables, we follow Grossman and Benham(1974) and Harkness(1996) by including a vector of regional dummies to account for regional price variation. As shown by Grossman and Benham(1974), the sign of the coefficients on these dummies should reflect the sign of the deviation from national average prices.[15] Following Disney and Gosling(1998) who found, using the BHPS, that public and private sector pay differs, particularly for women, we also include a binary variable to indicate workforce sector to distinguish between the public and private sectors.(JOBPRIV). It is possible, as found by Disney and Gosling(1998), that this variable is endogenous. Following Harkness(1996), we include a variable which measures the number of employees at the individual's place of work(JBSIZE).[16]

We also include indicators of marital status. Within a household production framework, it may be expected that due to household economies of scale, married/cohabiting individuals are able to devote more time, *ceteris paribus*, to labour market activities. Hence, we expect marital status to capture experience and productivity effects which are not captured by the variables already included. 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. Given that we restrict our sample to working individuals, this mechanism also leads us to expect a positive coefficient on the married/cohabiting indicator. Again, we allow for the exogeneity of this variable given the possibility of selection into marriage partially on the basis of unobserved characteristics which also affect wages. Finally we include a variable which measures the number of children aged between 0 and 4 years of age(KIDS04). Harkness(1996), using the 1992-1993 cross-section of the BHPS, measured the presence of children in the household using a binary indicator and found a positive and significant coefficient for men and a negative and significant coefficient for women. We also include a vector of binary variables to indicate occupational status(PROF,MANAG,SKLLNM,SKLLM). We assumed these variables to be endogenous given the likelihood of selection into job types on the basis of unobserved characteristics which also impact on wages. Finally, we include a vector of time dummies to control for aggregate productivity effects and inflation.

Time-invariant variables

For the exogenous time-invariant variables, Z_1, we include an indicator of ethnic status which is equal to one if the individual is white and zero otherwise(WHITE). As an indicator of educational attainment we follow Harkness(1996) and include indicators of the highest academic qualification achieved. We follow the categorisation of Harkness(1996) and split the sample into groups with a degree or higher(DEG), a Higher national diploma or equivalent(HNDCT), 'A' levels or equivalent(ALEVELS), and 'O' levels or equivalent(OLEVELS). The baseline category includes

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

[16]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.

those with no formal qualifications. Harkness(1996) found a gradient in wages which reflects this educational attainment gradient. [17] In order to reduce the demands on the data, we also employ an indicator of whether an individual has a degree or higher degree when utilizing the instrumental variable estimators. Although academic achievement is likely to be a reasonable indicator of unobserved ability, and hence we may be better able to control for the endogeneity of education than studies that have used years of schooling(e.g. Kim and Polachek(1993)), it remains an imperfect indicator. Furthermore, in addition to ability, there may be other unobserved variables correlated with academic attainment which are also correlated with wages, such as time preference and attitudes towards risk. Given our expectation that educational attainment is endogenous and the corroborative findings of previous work (e.g.Hausman and Taylor(1981), Cornwell and Rupert(1988), Baltagi and Khanti-Akom(1990)) we include DEG as an element of Z_2.

Following the work of Harkness(1996) who used the BHPS to estimate variations over time in the male-female earnings gap and found that the coefficients of the wage equations significantly differ by gender, we split our sample accordingly. Hildreth(1999) also splits his sample by gender and finds, in general, that the rates of return to individual characteristics are different for men and women. Kim and Polachek(1993) also split their sample and find the coefficients to differ.

Summary statistics for the full and fully-employed samples for both males and females are presented in table 1. The average wage for men is greater than for women, with full-time female earners receiving higher wages than female part-time workers. For males, the proportion of part-time observations is approximately 2%, while 33% of observations on females in the full sample are for part-time workers. Hence we would expect more variation in the results across the two samples for females than for males if parameters differ for full-time and part-time workers, while expecting negligible variation for males. Females appear to have a slightly higher score on the General Health Questionnaire, indicating slightly worse psychological well-being. Likewise, fewer observations on females indicate excellent self-assessed health; however similar proportions of observations on males and females indicate fair self-assessed health or worse. Also of interest is the differential in experience; males appear to have greater within-job experience than females. Females also appear less well qualified, are less likely to be employed in the private sector, and are more likely to be employed in skilled non-manual jobs, while males are more likely to be employed in skilled manual occupations.

5 Results

Males

We begin with the results for the full sample shown in table 2. Of particular interest are the coefficients on the endogenous variables. Beginning with the health variables we can see that worsening psychological health leads to a decrease in hourly wages, with the estimates remarkably robust across the alternative estimators. The coefficients on the self-assessed general health variables exhibit the expected signs and relative magnitudes, but are never significantly different

[17] Although we do not present the results obtained when including all educational categories, *GLS* estimation produced the expected educational gradient. Full results are available on request from the authors.

from zero at the 10% level. However, one feature is noteworthy; the within and instrumental variables estimates are consistently lower than the *GLS* estimate, with the within estimate on SAHEX 25% lower than that obtained using *GLS*. This may indicate positive correlation between the individual effects and self-assessed health, with those individuals that are more productive, or at least able to obtain relatively high wages, having unobserved characteristics which lead to better self-assessed health.[18]

Also of interest are the occupational status variables; as expected there is a gradient in wages which reflects occupational status. However, while the gradient remains apparent having accounted for endogeneity, and the parameter estimates lead us to reject the null hypotheses of zero coefficients, the absolute magnitudes are much diminished. A similar conclusion can be reached as for self-assessed health, although the difference between the *GLS* and within estimates are much larger; it appears that there is positive selection into occupational categories, which may reflect differing time preference, attitudes to risk or other unobserved factors which are positively correlated with wage rates.

The coefficient on DEG using the HT instrument set is around three times the magnitude of the *GLS* estimate. Noticeably, this differential diminishes as stronger exogeneity assumptions are employed using the AM and BMS estimators. However, an analogous, but opposing selection mechanism appears to be operating; those individuals that obtain a degree or higher degree appear to be compensating for unobserved characteristics which would otherwise reduce their wages. This result has also been obtained by Hausman and Taylor(1981), Cornwell and Rupert(1988), and Baltagi and Khanti-Akom(1990), and can be rationalised by considering a model where schooling or educational attainment is assumed to be endogenously determined, as considered by Griliches(1977). Further, our results bear a striking resemblance to those obtained by Cornwell and Rupert and Baltagi and Khanti-Akom. Using data from the Panel Study of Income Dynamics for a similar number of observations and time periods, and an analogous specification, they also found the majority of the efficiency gains from the AM and BMS estimators to be attached to the coefficient of the time-invariant endogenous variables, and the estimated coefficient to gradually approach the *GLS* estimates. In particular, the AM estimator reduces the standard error of the coefficient on DEG by around 30% relative to the HT estimator, while BMS adds an additional (empirical) efficiency gain of around 11% relative to the AM estimator. This result is to be expected; as the additional AM and BMS instruments are time-invariant, the majority of their additional explanatory power will impact on the time-invariant variables. There are however two important differences between the results obtained here and those of the authors mentioned above.

Firstly, the null hypothesis of no correlation between the individual effects and the explanatory variables was rejected in their applications. In our case we are unable to reject the null

[18] For all samples, we also experimented with the previous survey period values of psychological and general self-assessed health rather than health in the current period. In this case we lose the first time period observations from our sample. Although our preferred specification employs the current period values of the health variables, we do not extend the sample to all six waves as we lose some individuals through item non-response at wave one. Furthermore, this maintains sample comparability and allows the utilisation of the lagged training variable. In general the effect of the health variables is diminished when using previous period survey values: the GHQ variable is not significant for males, while the self-assessed health variables become insignificant for females, with the remainder of the coefficients showing little deviation. Full results are available on request from the authors.

of exogeneity, ($\chi^2(29) = 33.14$). However, the behaviour of the parameter estimates for self-assessed health, occupational status and educational attainment appears to justify scepticism concerning a 'literal' interpretation of this result. Furthermore, all of the instrument sets appear to be valid, enabling the use of the HT, AM, and BMS estimators. Interestingly, this implies that psychological and self-assessed health are, if correlated with the unobserved individual effect, correlated only through a time-invariant component. As can be seen from the table, with the exception of the coefficient on DEG, the precision of the estimators differs negligibly from that of *GLS*. Hence, the application of the HT, AM and BMS estimators allows us to obtain precise estimates, while avoiding the potential bias and inconsistency of the *GLS* estimator.

Secondly, the work of HT, Cornwell and Rupert and Baltagi and Khanti-Akom used years of schooling as their measure of education. In this application, we have used academic qualifications. Our findings, using a different dataset and measure of educational attainment, add weight to the hypothesis of a negative selection effect operating on educational attainment and wages.

Considering the exogenous variables, the estimated coefficients on AGE, AGESQRD, and EXP and EXPSQRD imply the expected significant concave and quadratic relationship with the logarithm of hourly wages. These coefficients are also robust to alternative estimation methods. The impact of the number of employees in the workplace also significantly increases wages, as does unionisation, with the expected positive differential between those that are union members and those non-members that are covered by union bargaining and negotiation. As found by Hildreth(1999), there appears to be no evidence of selection(positive or negative) for males. As found by Disney and Gosling(1998), the coefficients on the private sector dummy are positive but insignificant as are those for specific training in the previous period. The marital status estimates demonstrate substantial instability, but are never significant. Interestingly, and as observed for DEG, the coefficients tend towards the *GLS* estimates as we augment the instrument set using the HT, AM, and BMS estimators. This may indicate endogeneity which is gradually reintroduced through the implementation of estimators which require increasingly strong exogeneity assumptions, or it may reflect the relative inaccuracy of the within estimator due to few changes of marital status.

Our results for the fully-employed male sample presented in table 3 are very similar to those using the full sample, with one notable, and surprising exception. While the gradient in self-assessed health is maintained, the magnitudes of the coefficients on both the excellent and good self-assessed health variable are reduced, by 30-35% and 60-65% respectively. One explanation of this result is that part-time workers have a greater wage response to good or excellent health than full-time workers. However, given the simultaneous nature of the wage-labour supply relationship, an alternative explanation is that those individuals who choose part-time work do so because of the high wage they are offered. This in turn may lead to better health. Indeed Sundberg(1996) found a positive effect of reduced labour supply on self-assessed general health.

Females

Table 4 presents the results for females using the full sample. There are some noteworthy features of these results relative to those obtained using the comparable male sample. In particular, while we observe the same age-wage profile as for males, the coefficients on the experience variables are never significant. It appears that females do not receive the same compensation for within-job experience as males. Further, there is not a positive and significant effect of working in an establishment with many employees as was observed for males. There are also interesting differences with regard to the unionisation variables; while there is a similar gradient with respect to the extent of union attachment, the responses for females are larger than for males. Further, there appears to be(at least using the within estimate) substantial *positive* selection which accounts for around 35% of the *GLS* estimate. While this is qualitiatively and quantitatively in accord with some previous work(e.g. Chamberlain(1982)), it contradicts the results of Hildreth(1999) outlined earlier. However, as noted by Freeman(1984), the direction of bias due to measurement error when applying the within-groups estimator is dependent on the degree of that error; when it is modest and the proportion of individuals who change status is also modest the bias from utilisation of the within estimator is downward. However, given the use of the same dataset (although Hildreth used only private sector employees and an alternative construction of the hourly wage variable) and equivalent measures of union status this result is perplexing. Also of interest are the results for the private sector and number of children variables. Working in the private sector appears to decrease the wage of working women, although whether due to measurement error or positive selection into the public sector, this estimate is not significantly different from zero using the within estimator. This is in line with the results obtained by Disney and Gosling(1996). Also of interest is the impact of children in the household; taken literally the presence of children appears to increase hourly wages. This contradicts the *OLS* results obtained by Harkness(1996), who a found a significant negative impact using a binary indicator to capture the presence of children in the household. One explanation for this result is contamination due to endogeneity bias. However, the within and instrumental variable results differ little from the *GLS* estimates suggesting either pure simultaneity or a true positive impact of children in the household on hourly wages.

For females, the impact of the psychological health variable on hourly wages is negative, but insignificant. This is of particular interest as females, on average, report slightly worse pyschological health than males in our sample. However, for females, worsening psychological health does not appear to lead to significantly reduced wages. There are at least three alternative explanations of this result: i) differential reporting, (i.e. males under-report the presence or severity of psychological symptoms which are associated with productivity reduction), ii) productivity losses exist for males which are not apparent for females, or iii) differential discrimination regarding psychological health which favours females, perhaps due to societal and employer expectations.

For the self-assessed health variables similar results are found as for males; again while not significant a gradient appears to exist. Likewise, there is evidence of positive selection with the within estimates 40% and 12% lower than the *GLS* estimates for the excellent and good self-assessed variables respectively. The remainder of the results concerning the educational attainment variable and the validity and efficiency gains obtained from use of the HT, AM, and BMS estimators are equivalent to those found for the full-sample for males, and the previous discussion will not be repeated here. There is however one important exception: for females the null of no correlation between the individual effects and the explanatory variables is decisively rejected using a Hausman test, ($\chi^2(29) = 78.63$). This further justifies our use of the HT, AM and BMS estimators in this context.

Some features of the results for the fully-employed sample presented in table 5 are of particular interest. Firstly, the self-assessed health gradient is more pronounced, with the parameter estimate on excellent self-assessed health now positive and significant, at the 1% level using the *GLS* estimator and at the 10% level or below using the other estimators; excellent health appears to increase hourly wages by around 3%. It appears that excellent self-assessed health is of more value full-time workers than for part-time workers. Using the full-sample, the possibility of entering part-time work as a response to poor health is allowed, while those that maintain full-employment appear to accept a substantially lower hourly wage. It should be noted that this in direct opposition to the results obtained for males.[19] Second, the coefficients on union variables are much smaller in absolute magnitude, although the positive selection observed for the full sample is maintained. It appears that part-time workers achieve a larger wage increase from unionisation relative to the non-unionised than do full-time workers, both before and after accounting for potential selection effects. Third, the private sector 'penalty' observed for the full sample is not observed here; low part-time wages in the private sector appear to be driving the result observed for the full sample. Fourthly, the gradient by occupational status is not observed although the positive selection effect into high-status occupations is maintained. Finally, and in contrast to the results obtained for the full-sample for females, the null hypothesis of no correlation between the explanatory variables and the individual effects is not rejected using a Hausman test,($\chi^2(28) = 26.39$). However, as for males, the behaviour of the parameter estimates for self- assessed health, occupational status and educational attainment appear to justify scepticism concerning a 'literal' interpretation of this result. Furthermore, all of the instrument sets appear to be valid, enabling the use of the HT, AM, and BMS estimators. As can be seen from the table, with the exception of the coefficient on DEG, the precision of the estimators differs negligibly from that of *GLS*. Hence, the application of the HT, AM and BMS estimators allows us to obtain precise estimates, while avoiding the potential bias and inconsistency of the *GLS* estimator.

6 Conclusion

While income has been shown to positively affect health, little evidence has been offered for the impact of health on wage rates, particularly for developed economies. This paper considers the effect of self-assessed general and psychological health on hourly wages using longitudinal data from the six waves of the British Household Panel Survey. We employ single equation fixed effects and random effects instrumental variable estimators suggested by Hausman and Taylor(1981), Amemiya and MaCurdy(1986), and Breusch, Schmidt and Mizon(1989). Our results show that reduced psychological health reduces the hourly wage for males, while excellent self-assessed health increases the hourly wage for females. We also confirm the findings of previous work by Cornwell and Rupert(1988) and Baltagi and Khanti-Akom(1990), which suggested that the majority of the efficiency gains from the use of the instrumental variables estimators

[19] One approach to the discovery of the mechanisms leading to variations across the four samples is the application of simultaneous equations panel data methods such as suggested by Cornwell *et al.*(1992). However, these approaches to estimating a structural model of health, work-hours and wages require exclusion restrictions to identify the parameters of interest and are of greater computational complexity.

fall on the time-invariant endogenous variables, in our case academic attainment, and add further support to the hypothesis of a negative correlation between educational attainment and individual characteristics which affect wages.

However, some difficulties of interpretation remain. Firstly, while controlling for endogeneity due to correlation between included explanatory variables and the unobservable individual effects, we have not controlled for potential simultaneity. Hence, although our measures of health are to some extent, predetermined, our estimates may be contaminated by simultaneity bias as found in previous cross- sectional analyses. Secondly, our analysis has concentrated on the impact of health variation for the employed. Larger effects may be expected were we to extend our analysis to consider selective participation and allow for endogenous labour supply.

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Table 1: Variable means by sample and gender

	MALES		FEMALES	
	FULL SAMPLE	FULLEMP	FULL SAMPLE	FULLEMP
	$NT = 4295$	$NT = 4190$	$NT = 4055$	$NT = 2290$
WAGE	8.18	8.16	5.96	6.65
AGE	39.21	38.89	40.45	38.78
EXP	5.99	5.86	5.19	4.77
JBSIZE	296.17	299.81	216.40	259.40
SOUTHW	0.10	0.10	0.08	0.07
LONDON	0.09	0.09	0.10	0.11
MIDLAND	0.17	0.17	0.17	0.16
NORTHW	0.11	0.11	0.11	0.11
NORTHE	0.16	0.16	0.17	0.18
SCOT	0.08	0.08	0.10	0.10
WALES	0.05	0.05	0.04	0.04
COVMEM	0.44	0.44	0.38	0.44
COVNON	0.15	0.15	0.21	0.18
JOBPRIV	0.73	0.73	0.57	0.58
LJTRAIN	0.41	0.41	0.38	0.44
WIDOW	0.003	0.003	0.02	0.02
DIVSEP	0.04	0.04	0.09	0.10
NVRMAR	0.16	0.16	0.11	0.18
KIDS04	0.21	0.21	0.08	0.04
WHITE	0.98	0.98	0.98	0.98
DEG	0.15	0.15	0.11	0.15
OCSE	0.33	0.32	0.41	0.41
ALEVEL	0.23	0.23	0.14	0.16
HNDCT	0.08	0.08	0.07	0.09
HLGHQ1	10.14	10.14	11.59	11.48
SAHEX	0.31	0.31	0.26	0.28
SAHGD	0.53	0.52	0.55	0.54
PROF	0.09	0.09	0.03	0.03
MANAG	0.33	0.33	0.31	0.40
SKLLNM	0.15	0.14	0.41	0.39
SKLLM	0.30	0.30	0.07	0.08
JOBPT	0.02	-	0.33	-

Table 2: Males-Full Sample

$NT = 4295$	GLS	Within	HT	AM	BMS
AGE	.054	-	.051	.053	.053
	(.0075)	-	(.0077)	(.0075)	(.0075)
AGESQRD	-.056	-.052	-.051	-.055	-.056
	(.0087)	(.0108)	(.0091)	(.0088)	(.0088)
EXP	.005	.005	.005	.005	.005
	(.0018)	(.0020)	(.0019)	(.0019)	(.0019)
EXPSQRD	-.018	-.017	-.019	-.019	-.019
	(.0076)	(.0084)	(.0078)	(.0076)	(.0076)
JBSIZE	.00005	.00004	.00005	.00005	.00005
	(.00002)	(.00002)	(.00002)	(.00002)	(.00002)
COVMEM	.075	.075	.081	.078	.077
	(.0169)	(.0193)	(.0173)	(.1070)	(.0169)
COVNON	.028	.030	.030	.029	.029
	(.0148)	(.0164)	(.0152)	(.0149)	(.0149)
JOBPRIV	.015	.020	.020	.020	.018
	(.0216)	(.0258)	(.0224)	(.0218)	(.0217)
LJTRAIN	.008	.005	.007	.008	.008
	(.0070)	(.0076)	(.0072)	(.0071)	(.0070)
WIDOW	-.016	-.030	-.019	-.019	-.019
	(.0856)	(.0939)	(.0876)	(.0860)	(.0858)
DIVSEP	-.031	-.021	-.038	-.033	-.032
	(.0329)	(.0373)	(.0337)	(.0331)	(.0330)
NVRMAR	-.009	.007	-.012	-.010	-.009
	(.0217)	(.0248)	(.0222)	(.0218)	(.0218)
KIDS04	.010	.006	.007	.009	.009
	(.0099)	(.0109)	(.0102)	(.0100)	(.0100)
HLGHQ1	-.003	-.003	-.003	-.003	-.003
	(.0009)	(.0010)	(.0010)	(.0009)	(.0009)
SAHEX	.017	.013	.014	.014	.014
	(.0129)	(.0140)	(.0133)	(.0131)	(.0131)
SAHGD	.011	.010	.010	.010	.010
	(.0105)	(.0114)	(.0108)	(.0106)	(.0106)
PROF	.129	.075	.078	.087	.089
	(.0258)	(.0281)	(.0273)	(.0267)	(.0266)
MANAG	.115	.066	.070	.078	.080
	(.0200)	(.0225)	(.0212)	(.0208)	(.0207)
SKLLNM	.071	.033	.037	.044	.045
	(.0212)	(.0238)	(.0237)	(.0220)	(.0219)
SKLLM	.042	.035	.035	.037	.037
	(.0154)	(.0169)	(.0160)	(.0157)	(.0157)
WHITE	-.011	-	.134	.049	.032
	(.1310)	-	(.1383)	(.1336)	(.1328)
DEG	.378	-	1.19	.717	.623
	(.0580)	-	(.1985)	(.1389)	(.1236)
		$\chi^2(29) = 33.14$	$\chi^2(23) = 10.64$	$\chi^2(56) = 12.24$	$\chi^2(28) = 2.47$
Prob $> \chi^2$	-	.272	.987	.999	.999

1. $\sigma_\eta^2 = .038, \sigma_\alpha^2 = .386, \theta = .139$, based on consistent estimators of the variance components.
2. The year dummies, AGE, AGESQRD, SCOT and WALES were excluded from the instrument set for the AM and BMS estimators due to singularity.
3. Age was dropped from the within regression due to perfect collinearity with the year dummies.
4. Constant, year and regional dummies suppressed. Results are available from the authors on request.

Table 3: Males -Fully employed Sample

$NT = 4190$	GLS	Within	HT	AM	BMS
AGE	.063	-	.060	.062	.062
	(.0077)	-	(.0079)	(.0078)	(.0077)
AGESQRD	-.068	-.066	-.062	-.066	-.066
	(.0090)	(.0108)	(.0094)	(.0091)	(.0091)
EXP	.005	.005	.006	.005	.005
	(.0018)	(.0080)	(.0018)	(.0018)	(.0018)
EXPSQRD	-.018	-.016	-.018	-.017	-.017
	(.0075)	(.0080)	(.0074)	(.0073)	(.0073)
JBSIZE	.00005	.00004	.00005	.00005	.00005
	(.00002)	(.00002)	(.00002)	(.00002)	(.00002)
COVMEM	.077	.077	.081	.079	.079
	(.0165)	(.0187)	(.0168)	(.0166)	(.0165)
COVNON	.034	.035	.034	.034	.034
	(.0144)	(.0160)	(.0147)	(.0145)	(.0144)
JOBPRIV	.029	.037	.039	.032	.032
	(.0214)	(.0252)	(.0220)	(.0216)	(.0216)
LJTRAIN	.007	.004	.006	.006	.006
	(.0067)	(.0073)	(.0068)	(.0067)	(.0067)
WIDOW	-.015	-.023	-.017	-.017	-.017
	(.0815)	(.0896)	(.0830)	(.0818)	(.0817)
DIVSEP	-.031	-.027	-.036	-.032	-.031
	(.0317)	(.0356)	(.0323)	(.0318)	(.0317)
NVRMAR	.005	.017	.003	.004	.005
	(.0210)	(.0238)	(.0214)	(.0211)	(.0211)
KIDS04	.008	.006	.006	.007	.007
	(.0095)	(.0105)	(.0097)	(.0095)	(.0095)
HLGHQ1	-.002	-.002	-.002	-.002	-.002
	(.0009)	(.0010)	(.0009)	(.0009)	(.0009)
SAHEX	.011	.009	.009	.009	.009
	(.0124)	(.0135)	(.0127)	(.0125)	(.0125)
SAHGD	.004	.004	.004	.004	.004
	(.0101)	(.0110)	(.0103)	(.0102)	(.0102)
PROF	.117	.076	.078	.085	.086
	(.0250)	(.0279)	(.0262)	(.0257)	(.0256)
MANAG	.103	.065	.068	.075	.076
	(.0195)	(.0218)	(.0204)	(.0200)	(.0198)
SKLLNM	.059	.029	.033	.038	.039
	(.0206)	(.0230)	(.0216)	(.0212)	(.0211)
SKLLM	.035	.029	.030	.031	.031
	(.0148)	(.0163)	(.0153)	(.0150)	(.0150)
WHITE	.010	-	.169	.080	.064
	(.1489)	-	(.1568)	(.1519)	(.1511)
DEG	.381	-	1.19	.747	.657
	(.0650)	-	(.2010)	(.1494)	(.1350)
		$\chi^2(29) = 19.54$	$\chi^2(23) = 7.03$	$\chi^2(56) = 10.03$	$\chi^2(28) = 1.18$
Prob $> \chi^2$	-	.907	.999	.999	.999

1. $\sigma_\eta^2 = .035, \sigma_\alpha^2 = .494, \theta = .118$, based on consistent estimators of the variance components.
2. See notes 2, 3 and 4 for table 2.

Table 4: Females -Full Sample

$NT = 4055$	GLS	Within	HT	AM	BMS
AGE	.033	-	.030	.031	.031
	(.0077)	-	(.0079)	(.0078)	(.0078)
AGESQRD	-.095	-.046	-.040	-.041	-.042
	(.0092)	(.0120)	(.0095)	(.0093)	(.0093)
EXP	.0007	.0003	.001	.001	.001
	(.0023)	(.0025)	(.0023)	(.0023)	(.0023)
EXPSQRD	-.009	-.009	-.011	-.010	-.010
	(.0099)	(.0108)	(.0101)	(.0100)	(.0100)
JBSIZE	.00001	.00001	.00002	.00002	.00001
	(.00002)	(.00002)	(.00002)	(.00002)	(.00002)
COVMEM	.087	.059	.080	.083	.084
	(.0191)	(.0221)	(.0196)	(.0193)	(.0192)
COVNON	.055	.043	.058	.057	.057
	(.0162)	(.0181)	(.0166)	(.0164)	(.0163)
JOBPRIV	-.046	-.020	-.019	-.028	-.033
	(.0192)	(.0228)	(.0205)	(.0199)	(.0197)
LJTRAIN	.008	.001	.006	.006	.007
	(.0082)	(.0088)	(.0084)	(.0083)	(.0082)
WIDOW	-.018	.0002	-.037	-.032	-.028
	(.0553)	(.0659)	(.0565)	(.0559)	(.0556)
DIVSEP	.003	.004	.004	.003	.002
	(.0263)	(.0307)	(.0268)	(.0266)	(.0265)
NVRMAR	-.032	-.043	-.041	-.038	-.036
	(.0271)	(.0318)	(.0277)	(.0274)	(.0272)
KIDS04	.051	.042	.047	.048	.049
	(.0168)	(.0183)	(.0171)	(.0169)	(.0169)
HLGHQ1	-.0009	-.0008	-.0007	-.0007	-.0007
	(.0009)	(.0010)	(.0009)	(.0009)	(.0009)
SAHEX	.018	.011	.013	.014	.015
	(.0138)	(.0149)	(.0143)	(.0141)	(.0141)
SAHGD	.012	.010	.010	.010	.011
	(.0107)	(.0115)	(.0110)	(.0109)	(.0108)
PROF	.151	.021	.050	.062	.068
	(.0383)	(.0432)	(.0410)	(.0404)	(.0401)
MANAG	.150	.051	.068	.076	.082
	(.0229)	(.0268)	(.0255)	(.0251)	(.0249)
SKLLNM	.058	-.016	-.006	.001	.005
	(.0218)	(.0257)	(.0246)	(.0242)	(.0240)
SKLLM	.061	.047	.052	.052	.052
	(.0237)	(.0261)	(.0250)	(.0247)	(.0245)
WHITE	-.056	-	.035	.006	-.011
	(.1262)	-	(.1302)	(.1283)	(.1276)
DEG	.377	-	1.05	.830	.697
	(.0838)	-	(.1710)	(.1367)	(.1223)
		$\chi^2(29) = 78.63$	$\chi^2(23) = 27.94$	$\chi^2(46) = 6.77$	$\chi^2(28) = 5.96$
Prob $> \chi^2$	-	.000	.218	.999	.999

1. $\sigma_\eta^2 = .044, \sigma_\alpha^2 = .262, \theta = .180$, based on consistent estimators of the variance components.
2. The year dummies, AGE, AGESQRD, SCOT, WALES, NORTHW and NORTHE were excluded from the instrument set for the AM and BMS estimators due to singularity.
3. See notes 3 and 4 for table 2.

Table 5: Females -Fully Employed Sample

$NT = 2290$	GLS	Within	HT	AM	BMS
AGE	.044	-	.041	.042	.043
	(.0093)	-	(.0095)	(.0094)	(.0093)
AGESQRD	-.056	-.052	-.051	-.054	-.054
	(.0114)	(.0137)	(.0116)	(.0115)	(.0114)
EXP	.004	.004	.004	.004	.004
	(.0026)	(.0028)	(.0026)	(.0026)	(.0026)
EXPSQRD	-.014	-.016	-.015	-.015	-.015
	(.0108)	(.0117)	(.0109)	(.0108)	(.0108)
JBSIZE	.00002	.00002	.00002	.00002	.00002
	(.00002)	(.00002)	(.00002)	(.00002)	(.00002)
COVMEM	.041	.016	.035	.038	.039
	(.0226)	(.0259)	(.0230)	(.0227)	(.0227)
COVNON	.008	-.010	.008	.008	.008
	(.0200)	(.0223)	(.0203)	(.0201)	(.0201)
JOBPRIV	-.015	.028	.008	-.005	-.007
	(.0268)	(.0325)	(.0286)	(.0275)	(.0274)
LJTRAIN	.014	.008	.012	.013	.013
	(.0090)	(.0097)	(.0091)	(.0090)	(.0090)
WIDOW	.026	.060	.0001	.013	.016
	(.0737)	(.0835)	(.0748)	(.0739)	(.0738)
DIVSEP	.003	-.005	.004	.002	.002
	(.0271)	(.0305)	(.0274)	(.0272)	(.0271)
NVRMAR	-.004	-.003	-.009	-.006	-.006
	(.0265)	(.0305)	(.0268)	(.0266)	(.0265)
KIDS04	-.022	-.021	-.019	-.021	-.021
	(.0249)	(.0270)	(.0251)	(.0249)	(.0249)
HLGHQ1	-.0009	-.0009	-.0008	-.0008	-.0008
	(.0010)	(.0011)	(.0010)	(.0010)	(.0010)
SAHEX	.031	.027	.028	.028	.029
	(.0152)	(.0165)	(.0156)	(.0154)	(.0154)
SAHGD	.018	.016	.017	.017	.017
	(.0121)	(.0130)	(.0123)	(.0122)	(.0121)
PROF	.065	-.021	-.001	.005	.011
	(.0438)	(.0490)	(.0458)	(.0452)	(.0450)
MANAG	.109	.045	.055	.058	.061
	(.0315)	(.0358)	(.0337)	(.0332)	(.0331)
SKLLNM	.038	-.014	-.007	-.008	-.004
	(.0317)	(.0363)	(.0341)	(.0336)	(.0335)
SKLLM	.061	.047	.048	.050	.049
	(.0314)	(.0347)	(.0327)	(.0323)	(.0323)
WHITE	.028	-	.089	.058	.052
	(.1616)	-	(.1648)	(.1626)	(.1624)
DEG	.341	-	.818	.558	.511
	(.0689)	-	(.1921)	(.1329)	(.1232)
		$\chi^2(28) = 26.39$	$\chi^2(23) = 11.98$	$\chi^2(41) = 4.54$	$\chi^2(28) = 3.61$
Prob $> \chi^2$	-	.552	.971	.999	.999

1. $\sigma_\eta^2 = .032, \sigma_\alpha^2 = .306, \theta = .144$, based on consistent estimators of the variance components.
2. The year dummies, AGE, AGESQRD, SCOT, WALES, SOUTHW, NORTHW and NORTHE were excluded from the instrument set for the AM and BMS estimators due to singularity.
3. See notes 3 and 4 for table 2.