There Is No Gain In Pain: Psychological Well-Being, Participation, and Wages in the BHPS*

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Abstract

Thanks to a recent estimator that allows to account for endogeneity, unobserved heterogeneity, and sample selection in an unified framework, we investigate the effect of psychological well-being on wages and labour market participation. Using a panel from the British Household Panel Survey, we find the effect of mental health on labour market outcomes to differ across gender. In particular, mental distress significantly reduces participation across genders, but, conditional on participation, has a significant negative effect on hourly wages only in the female sample.

Keywords: self-assessed mental health; GHQ; sample selection; endogeneity; social support network; BHPS; participation.

JEL Classification: I10, C23, H51

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1 Introduction

According to the UK Labour Force Survey, almost one million female employees and more than 500 thousands male employees aged 16-64 reported at least one condition related to mental functioning in 2017. This corresponds to approximately 6.7% and 3.5% of the UK labour force, and follows a continual growth over recent years. The Adult Psychiatric Morbidity Survey, a household survey funded by the Department of Health and partly conducted by clinically-trained research interviewers, shows that this might be an underestimation: the last figures available say that in 2014 one English adult in six showed symptoms of a common mental disorder, with women more likely to be affected than men (one in five females versus one in eight males). These rates seem to be different across employment status: employed people aged 16-64 had a common mental disorder rate which was half that of their non-employed counterparts (14.1% of those in full-time employment compared with 28.8% of unemployed people, and 33.1% of the economically inactive). Given the magnitude of these numbers, it is no surprise then that poor mental health has been estimated to have a considerable economic impact. The Centre for Mental Health, for example, estimates that mental illness is one of the largest single causes of sickness absence in the UK, accounting for 91 million sick days in 2017 and a total cost to employers at nearly £35 billion each year. Since these figures, however, take into account neither the effect of mental illness on employment, nor the losses in productivity due to employees functioning at less than full capacity, the public cost of mental health problems is certainly higher.

Understanding the relationship between mental health and labour market outcomes is necessary in order to outline the relative cost of mental illness for society and to assess the outcomes of social policies carried out to improve people's mental health. However, studying this relationship presents several challenges. Firstly, while psychological well-being is likely to affect labour productivity and thus wages, one could also expect a reverse effect from employment to mental health. Secondly, unobserved individual factors, like childhood circumstances and cognitive ability, could be correlated with both mental health status and labour market outcomes. Thirdly, a problem of measurement error in mental health status arises, since researchers usually need to rely on self-assessed measures. Finally, non random sample selection may result in inconsistent estimation of the effect of mental health status on income, if one fails to take into account that labour market participation is itself influenced by mental health status.

In this paper, we investigate the relationship between a self-assessed measure of mental health status and average hourly wages for both male and female samples, which we construct from the British Household Panel Survey. To overcome the numerous challenges listed above, we apply a series of different estimators to our longitudinal dataset. Most importantly, for the first time in the study of the effect of psychological well-being on wages, we account for correlated individual effects, endogeneity of the mental health variable, and sample selection, in an unified framework. In order to do so, we employ the estimator proposed by Semykina and Wooldridge (2010). In line with previous literature, we instrument the endogenous dependent variable, mental health, with the perceived social support network available to the respondent.

As expected, we find signs of endogeneity for the mental health variable. Indeed, we show that measurement errors lead to an underestimation of the true effect of mental distress on labour market outcomes. Conversely, the correlation between the mental health variable and the unobservable individual effects is associated with an upward bias. We perform several tests that indicate that correcting for sample selection in the labour force is necessary at least for the female sample. We find that psychological well-being significantly affect labour market participation across genders: individuals that may be suffering from mental distress are between 6 and 20 percentage points less likely to be employed. Conversely, mental distress has a significantly negative effect on wages only for the female sample: the wage gap between a non-distressed and a distressed female may be as high as 1£ per hour.

The remainder of this paper proceeds as follows. Section 2 reviews the existing literature. Section 3 presents our estimation procedures, while Section 4 describes the dataset and the variables of interest. Section 5 shows the results of the econometric analysis. Finally, Section 6 concludes.

2 Literature Review

Various measures of health status have been included as determinant of earnings at least since Luft (1975). Specifically, however, the pioneering study of the impact of mental health on labour market outcomes is due to Bartel and Taubman (1979), who, using data on white male twins born between 1917 and 1927, found negative and long-term effects of psychoses and neuroses on wages, employment, and hours worked.

More recent papers have taken into account the potential endogeneity of mental health status and labour market outcomes, and thus used two-stage instrumental variables models. Variables that have been used as instruments for mental health in this large literature include: parental history of mental health and substance problems (Mullahy and Sindelar, 1996, Ettner et al., 1997, Marcotte et al., 2000, Marcotte and Wilxox-Gok, 2003, Renna, 2008, Chatterji et al., 2011), earlier onset of psychiatric disorders or substance use (Ettner et al., 1997, Chatterji et al., 2007, Renna, 2008, Chatterji et al., 2011, Banerjee et al., 2017), presence of physical chronic conditions (McCulloch, 2001, MacDonald and Shields, 2004, Banerjee et al., 2017), participation in physical activity (Hamilton et al., 1997), religiosity (Heien, 1996, Hamilton and Hamilton, 1997, Alexandre and French, 2001, McCulloch, 2001, MacDonald and Shields, 2004, Chatterji et al., 2007), recent stressful events (Hamilton et al., 1997, Frijters et al., 2014), and state-level alcohol and illicit drug policies and prices (Barrett, 2002, DeSimone, 2002). Similarly to our paper, measures of the perceived social support network available to the respondent have been used to instrument mental health status by Hamilton et al. (1997), Alexandre and French (2001), and Ojeda et al. (2010).

Most of these papers, however, only study the relationship between mental health status and labour market participation. Only few papers have also considered the impact of mental illness on wages, like we do. Among these are Ettner et al. (1997), Marcotte et al. (2000), and Chatterji et al. (2011), who all use data from the National Comorbidity Survey, a large-scale field survey of mental health in the United States. Ettner et al. (1997) found that psychiatric disorders significantly reduced employment and income for both men and women, but the effect on income is found to be very sensitive to the estimation method. Marcotte et al. (2000) showed that depression negatively impacts women's employment and incomes but is less consistently associated with men's reduced incomes and participation. Chatterji et al. (2011) found no effects of recent psychiatric disorder on earnings among employed individuals; however, the effect on labour force participation and employment is negative for both females and males. Conversely, Contoyannis and Rice (2001) study, like we do, the effect of mental health on income in the British Household Panel Survey: they find that worsening psychological health decreases hourly wages for males only. However, they do not consider self-selection nor the impact of mental health status on labour market participation.

In our paper, we use the recent estimator proposed by Semykina and Wooldridge (2010) to control for endogeneity, selection bias, and unobserved heterogeneity in one framework, allowing us to study the effect of mental health on both labour market participation and income. As far as we know, this estimator has been only used in this context by Jäckle and Himmler (2010). Using data from the German Socio-Economic Panel, they find a statistically significant effect of physical health on wages only for men, while for women a significant effect on labour market participation is found. However, they do not investigate the effect of mental health status.

3 Econometric Method and Issues

The aim of this paper is to gauge the relationship between psychological well-being and wages for the entire population, and not only for those individuals who are employed. Therefore, we formally specify our model as follows:

$$w_{it}^{*} = \beta_0 + \boldsymbol{x}_{it}\boldsymbol{\beta}_1 + \boldsymbol{y}_{it}\boldsymbol{\beta}_2 + \alpha_i + \eta_{it} \tag{1a}$$

$$w_{it}^{*} = w_{it}, \quad y_{it}^{*} = y_{it} \quad \text{if } S_{it} = 1 \quad \text{and unobserved otherwise} \tag{1b}$$

$$S_{it}^{*} = \gamma_0 + \boldsymbol{z}_{it}\boldsymbol{\gamma}_1 + k_i + e_{it} \quad \text{with } S_{it} = 1 \text{ if } S_{it}^{*} > 0 \tag{1c}$$

where w_{it}^{*} is a measure of hourly wage of individual $i = 1, ..., N$ at time $t = 1, ..., T_i$, $\boldsymbol{\beta}_1$ is a vector of parameters associated with $\boldsymbol{x}_{it}$ vectors of independent variables (including mental health condition) that can be observed for all the individuals in the samples and $\boldsymbol{\beta}_2$ is a vector of parameters associated with $\boldsymbol{y}_{it}$ vectors of variables that can be observed only if the individual works. α_i is a vector of unobservable time-invariant individual characteristics, whereas η_{it} is a mean zero unobserved error term. The wage equation in (1a) is a Mincer's (1974) earnings equation, modified to account for the impact of mental health and other variables and for the panel structure of the dataset.

As stated in (1b), we observe w_{it}^* only if the individual participates to the workforce, i.e. only if $S_{it} = 1$, where S_{it} denotes market participation. Equation (1c) indicates that we observe participation to the labour market only if the latent variable S_{it}^*, which represents the unobservable individual propensity to work, is positive. This depends on $\boldsymbol{z}_{it}$ where $\boldsymbol{z}_{it}$ is a superset of $\boldsymbol{x}_{it}$. The individual heterogeneity k_i is normally distributed with mean equal to zero and variance σ_t^e.

In the estimation of the relationship between health and wages, one faces a series of issues. Indeed, mental health is likely to be endogenous, due to measurement errors, omitted variables, and reverse causality. Firstly, due to the lack in the BHPS of an objective measure that can easily capture mental health in quantitative terms, we need to resort to a self-assessed measure, which is likely to contain inaccuracies. Secondly, mental health can be correlated with unobserved characteristics which can also affect productivity and hence wages (e.g. genetic endowment). The consequence is a non zero correlation between the health regressor and the error component. Thirdly, the direction of the relationship between health and wages can be reversed: if investment in health increases with salary, health should rise with wages (Grossman, 2001). This leads to a correlation between health and the period and individual specific error component of wages, η_{it}.[1]

Another potential issue is selection bias. Selection is not an issue if, for example, the decision to participate in the labour market is randomly determined. This is unlikely to be the case, as we expect some of the factors that determine participation to also influence

[1]Simultaneity can arise if wages influence health contemporaneously or with a lag in the presence of serial correlation in η_{it}.

mental health and income. We will correct for sample selection below, but, for the time being, we start our analysis by disregarding the selection problem, and thus by estimating the wage equation in (1a) in isolation. Below is our estimation strategy.

We first estimate the wage equation by Pooled OLS using cluster robust standard errors to account for cluster heteroskedasticity. If the regressors are not correlated with the errors, the estimator is unbiased, consistent, and efficient. Secondly, we implement a within (FE) and a generalised least squares (GLS) regression with cluster robust standard errors. In the first case, we assume that the regressors are uncorrelated with the idiosyncratic error but we do not make any assumptions on the unobserved heterogeneity. The within estimator, in fact, will be unbiased and consistent as N and/or T tend to infinity even if the regressors are correlated with α_i. Contrarily, in the second case we assume that all the regressors are uncorrelated with both the error components. If this was the case, the GLS could be considered more efficient because it exploits the information on the orthogonality conditions between the exogenous regressors and α_i; however, as explained above, we suspect the mental health variable to be endogenous. In order to test the validity of the orthogonality conditions, we perform a cluster robust version of the Hausman's overidentifying restrictions test on the additional restrictions imposed by the GLS estimator. The test is asymptotically distributed as $\chi^2 k$.[2] If the corresponding Hansen-Sargan J statistic is higher than the relative critical value, we reject the null hypothesis that the additional orthogonality conditions hold. In this case, the FE estimator is more reasonable.

Thirdly, we implement a two stage least squared (2SLS) and a within-2SLS (FE-2SLS) regression with cluster robust standard errors. We run these two instrumental variable approaches (IV) in order to deal with the endogeneity problem. IV requires the use of an instrument, i.e. a regressor that is predictive of the potentially endogenous mental health status but that is otherwise independent of the dependent variable of interest (here, the

[2] Since we use the cluster robust version of the test, the degrees of freedom k are given by $L^e - L^c$ where, L^e represents the number of orthogonality conditions used by the efficient but restricted estimators (in our case, GLS) and L^c represents the number of orthogonality conditions used by the unrestricted (consistent but inefficient) estimator (here, FE). Thus, $L^e - L^c$ represents the number of orthogonality conditions being tested (Baum et al., 2006).

labour market outcomes). Following previous literature, we instrument mental health status using a proxy for the perceived social support network of the individual. We test the validity of the instrument using Hansen-Sargan's test of overidentifying restrictions.

At this point, it remains to deal with one last source of econometric bias, namely the presence of sample selection. Thus, in the last step, we run a regression based on Semykina and Wooldridge's (2010) estimator. We choose this particular strategy because, among the several estimators that one can use to address the problem of selection bias in a panel setting, the one proposed by Semykina and Wooldridge (2010) not only allows for endogenous regressors but also does not require any known distribution of the errors in the equation of interest and the participation equation.

To do so, we first follow Mundlak (1978), Chamberlain (1982), and Wooldridge (1995), and explicitly model the correlation between the regressors and the unobserved heterogeneity. In particular, we write k_i as a linear combination of a constant term, the group-means of the time-varying regressors in $\boldsymbol{z}_{it}$ (the so-called Mundlak effects) and a normally distributed error term a_i. Therefore, the participation equation in (1c) is updated to

$$S_{it}^{*} = \gamma_0 + \boldsymbol{z}_{it}\boldsymbol{\gamma}_1 + \bar{\boldsymbol{z}}_i\boldsymbol{\theta} + \nu_{it}, \tag{2}$$

where $\nu_{it} = e_{it} + a_i$ is an error term, independent from $\boldsymbol{z}_{it}$ on which, as for η_{it}, no restrictions are imposed in terms of heteroskedasticity and serial correlation.

Two assumptions are required to implement the estimator proposed by Semykina and Wooldridge (2010). The first one is that η_{it} is a linear function of ν_{it} and mean independent of $\bar{\boldsymbol{z}}_i$ conditional on ν_{it}. The second is that α_i is modelled as in Mundlak (1978) and Chamberlain (1982) as a sum of a constant, the group-means, and an error b_i. Since we think that our variables of interest, mental health status, may be correlated with η_{it}, as it stands the first assumption is unfortunately not satisfied. In fact, mental health is included in $\boldsymbol{z}_{it}$, but $\boldsymbol{z}_{it}$ and η_{it} should not be correlated. For this reason, we remove the mental health variable from $\boldsymbol{z}_{it}$, where it is substituted with the instrument, which is assumed to be uncorrelated with η_{it}. This new vector, i.e. $\boldsymbol{z}_{it}$ where the mental health variable is substituted by the instrument, is called $\boldsymbol{q}_{it}$; its time averages are indicated with

$\bar{\boldsymbol{q}}_i$.

Having done all these steps, the following equation is obtained:

$$w_{it}^* = \varphi_0 + \boldsymbol{x}_{it}\boldsymbol{\beta}_1 + \bar{\boldsymbol{q}}_i\boldsymbol{\varphi}_1 + \boldsymbol{y}_{it}\boldsymbol{\beta}_2 + \bar{\boldsymbol{y}}_i\boldsymbol{\varphi}_2 + \xi_t\lambda_{it} + r_{it}. \tag{3}$$

In equation (3), we substituted $\bar{\boldsymbol{x}}_i$ with $\bar{\boldsymbol{q}}_i$ in order to satisfy Semykina and Wooldridge's (2010) requirement that η_{it} be uncorrelated with $\bar{\boldsymbol{z}}_i$. Moreover, r_{it} is the sum of b_i and l_i where the latter is the remaining part of η_{it} after including the Inverse Mills Ratios (IMRs), λ_{it}. These are obtained estimating T probit models of equation (2). As there is nothing preventing λ_{it} to be correlated with r_{is} for $s \neq t$, equation (3) can then be estimated using a Pooled 2SLS regression where $\bar{\boldsymbol{q}}_i$, $\boldsymbol{y}_{it}$, $\bar{\boldsymbol{y}}_{it}$ and λ_{it} are used as instruments. As suggested by Semykina and Wooldridge (2010), we build standard errors robust to heteroskedasticity and serial correlation.

4 Data

The data used in this analysis are taken from the British Household Panel Survey (BHPS). The data are provided by the UK Data Services and include information on the social, demographic, and economic characteristics of a representative sample of UK households. The BHPS started in 1991 with 5,500 households and 10,300 individuals drawn from 250 areas of Great Britain. In 1999, additional samples of 1,500 households in each of Scotland and Wales were added to the main sample; in 2001 an additional sample of 2,000 households was added in Northern Ireland. In 2010, more than 80% of the BHPS participants were merged into Understanding Society, a new survey which unfortunately lacks some of our variables of interest (especially, those about the social support network of the respondent).

We construct an unbalanced panel using the available 238,996 observations from the BHPS. Unfortunately, questions regarding the respondent's social support network (one of our instruments) are asked only once every two years: we thus limit our analysis to nine biennial waves covering the period between 1991 and 2007. We drop individuals who, in a given year, are self-employed, retired, still in education, in maternity leave, or attending a government training scheme. To allow for heterogeneity in coefficients across gender, we split the sample between men and women. In line with the State Pension age in the years covered, we only consider males aged between 16 and 65 years and females aged between 16 and 60 years at the time of the interview.

After excluding individuals who did not give valid answers for the variables used in the estimations, we obtain a sample of 62,686 observations (of which 31,413 males and 31,273 females), for a total of 7,991 individuals who on average completed 5.04 waves. For those estimators which do not account for self-selection, we consider only those individuals in employment at the date of the interview. This restricted sample consists of 54,496 employees (26,670 males and 27,826 females). We refer the interested reader to Appendix Table A1 for more details about the stepwise construction of our sample.

4.1 Dependent Variables

Since the BHPS does not provide a measure of hourly wage, we construct it as a weighted average of the gross usual monthly wage from first and second job. First, we obtain the hourly wage in the main job by dividing the usual gross monthly pay by the number of hours worked per month for the main work, including paid overtime. Analogously, we calculate the hourly wage for the individuals who have a secondary job. We then construct an overall average wage by taking a weighted average of the hourly wage in the main and the secondary jobs. The weights correspond to the proportions of total working time spent in each type of job. We find the average hourly wage to be higher for males (£9.62) than for females (£7.63).

Finally, we calculate the inverse hyperbolic sine transformation (IHS) of the wage. The IHS transformation precisely approximates the logarithmic one and has the advantage of being defined for zero and negative values. In this way, the regression estimates are improved: the outliers influence is damped down and, thus, heteroskedasticity is ameliorated (see Georgarakos et al., 2014 and Pence, 2006 for more details).

Participation in the labour market is determined by the current employment status of the respondent.[3]

4.2 Health Variable

Our main independent variable is a measure of mental health, which we suppose endogenous. It consists of a reduced version of the General Health Questionnaire (GHQ), a self-administered psychometric screening tool originally used to screen for minor psychiatric disorders and now used as an indicator of subjective psychological well-being. The version in the BHPS is the widely used GHQ-12, which consists of the following 12 questions: (i) "Have you recently been able to concentrate on whatever you're doing?", (ii) "Have you recently lost much sleep over worry?", (iii) "Have you recently felt that you were playing a useful part in things?", (iv) "Have you recently felt capable of making decisions about things?", (v) "Have you recently felt constantly under strain?", (vi) "Have you recently felt you couldn't overcome your difficulties?", (vii) "Have you recently been able to enjoy your normal day-to-day activities?", (viii) "Have you recently been able to face up to problems?", (ix) "Have you recently been feeling unhappy or depressed?", (x) "Have you recently been losing confidence in yourself?", (xi) "Have you recently been thinking of yourself as a worthless person?", and (xii) "Have you recently been feeling reasonably happy, all things considered?".

Half of the items in the GHQ are "positively" worded, the other half are "negatively" worded. The available responses to negative items are: "Not at all", "No more than usual", "Rather more than usual", and "Much more than usual"; positive items have as possible responses: "Better than usual", "Same as usual", "Less than usual", and "Much less than usual". All items are rescored so that a low score is indicative of high psychological well-being, while higher scores indicate greater mental distress. The most

[3] There are three measures of current employment status in the BHPS: that on the Household Composition Form; that arising from the direct status question; and that arising from the sequence of questions about whether the respondent did any paid work in the last week, whether away from a job, and whether seeking work. Since the first of these is likely to be reported by someone else, we ignore it. In order to select all those in employment, we use the last measure, as suggested by Taylor et al. (2018). The second measure, indeed, is a self-defined status: the inconsistencies in our panel, however, are small (approximately 350 observations) and the results are qualitatively the same.

common way to summarise these answers is by using a bimodal score: this is obtained by counting the number of questions to which the individual responds in the worse two categories, giving a 12 point "Caseness" score.[4] This measure is increasingly being used in economics studies.[5]

We invert the Caseness score so that our measure of psychological well-being is decreasing in mental distress and ranges from 0 (the most distressed) to 12 (the least distressed). We then use a parallel transformation of the log function. In particular, we follow Jäckle and Himmler (2010) and we transform this scale, h_{it}, as follows,

$$MentalHealth_{it} = \ln\left(h_{it} + \sqrt{h_{it}^2 + 1}\right).$$

This choice is motivated by pragmatical reasons, as it allows us to use only one instrument when applying an instrumental variable approach and to maintain the non-linear structure suggested by earlier literature; moreover, it is defined for zero values.

The observed means (and standard deviations) of *Mental Health* are 3.00 (0.42) for working males and 2.91 (0.55) for working females. These values decrease to 2.67 (0.80) and 2.45 (0.95) for unemployed males and females, respectively. Standard t-tests confirm that the nonworking groups have statistically different (lower) means of this psychological well-being variable than the working groups ($t = 42.98$ with p-value $= 0.0$ for males and $t = 41.38$ with p-value $= 0.0$ for females), and thus are more distressed. Moreover, females have a statistically significant lower score in the transformed Caseness score ($t = 20.64$ with p-value $= 0.0$), which means that their psychological well-being is worse than males.

[4] This term refers to the use of cut off points to divide the population of interest into "normals" and "cases", where the latter expresses a higher probability that the respondent might be found to have a psychiatric illness at further investigation. Clinical studies usually argue that a cut-off point of 3 or 4 best discriminates between the two groups. We use the cut-off of 4 to facilitate readability of our results in Section 5.

[5] For example, the GHQ-12 has been used to study the relationship between mental health and financial behaviour (Brown et al., 2005), income inequality (Wildman, 2003), commuting (Roberts et al., 2011), promotion (Boyce and Oswald, 2012), education (Cornaglia et al., 2015), stock prices (Ratcliffe and Taylor, 2015), and crime (Dustmann and Fasani, 2015).

4.3 Instrument

When required, we instrument psychological well-being with a proxy for the social capital of the respondent. We construct this proxy by considering the perceived social support network available to the individual. In particular, we use the answers to the following questions available in the BHPS: (i) "Is there anyone who you can really count on to listen to you when you need to talk?", (ii) "Is there anyone who you can really count on to help you out in a crisis?", (iii) "Is there anyone who you can totally be yourself with?", (iv) "Is there anyone who you feel really appreciates you as a person?", and (v) "Is there anyone who you can really count on to comfort you when you are very upset?". For each question, we assign 1 if the answer is positive, and 0 if the individual does not have anyone to support him/her or is unsure. Our proxy for the social support network of the individual is obtained by summing up the responses to these questions.[6]

The resulting *Social Support* variable has an observed mean (and standard deviation) of 4.68 (0.90) for working males and 4.83 (0.65) for working females. These values decrease to 4.38 (1.28) and 4.54 (1.10) for unemployed males and females, respectively. Standard t-tests confirm that females have a highly significant stronger support network than males (also controlling for employment status), and that unemployed individuals have a highly significant weaker support network than employed ones (also controlling for sex).

4.4 Other Regressors

We include in the analysis a full set of socio-demographic characteristics. We control for the marital status, considering as the baseline category those individuals who are married, have a civil partner, or live as couple. We include the number of children in the household aged between 0 and 4 years, and a dummy indicating the presence of dependent children with more than 4 years in the household. As an indicator of educational attainment,

[6] Following previous literature, we also investigated various measures of religiosity and volunteering activities, but did not find them predictive of mental health in our panel. We also investigated including in our measure of social capital a variable counting the number of organisations the respondent is an active member in (excluding unions). Moreover, we tried different functional forms of the included instrument. Since results are qualitatively and quantitatively similar to the one showed here, we decided to not include them: these, however, are available on request.

we include a dummy variable which indicates if the individual has a degree or a higher education attainment. We also include a dummy variable indicating if the individual is white. Finally, a vector of time dummies to control for inflation and aggregate productivity effects and a dummy to account for living in the capital are also included.

An additional set of variables is used when estimating the wage equation. To capture the concavity of the earnings function, we include third degree polynomials of age and experience. We also include a vector of dummy variables indicating the occupational status of the individual, if the individual is employed in the private sector, and if the individual has undertaken any training or education related to her current job in the previous year. We account for the presence of a trading union at the individual's workplace and for being a member of this union. Finally, we include a continuous variable which measures the number of employees at the employee's workplace.

The exclusion restrictions, i.e. those variable that drive participation in the labour market but can be reasonably omitted from the wage equation, that we use are: the IHS transformation of non-labour income, a dummy variable for having a partner, partner's monthly gross pay, partner's education, and third degree polynomials of the partner's age and labour market experience.

Variable definitions are in Appendix Table A2. Summary statistics are presented separately for males and females in Appendix Tables A3 and A4.

5 Results

5.1 Participation equation

Since our hypothesis is that mental health influences participation as well as wages, in Appendix Tables A5 and A6 we present the results of several estimations of the participation equation, separately for men and women. Across all specifications we employ cluster robust standard errors.[7]

[7] In this paper, we used Stata 15 by StataCorp (2017) and the following user-written programs: Baum et al. (2002) and Schaffer (2005).

In the first two columns, we display Pooled OLS and FE results. In the third and fourth columns, we present the results from the 2SLS and FE-2SLS regressions, where the social support network of the individual is used as an instrument for her psychological well-being (see Section 4.3).[8] The mental health variable turns out to be statistically significant across all linear specifications for both males and females: an improve in the psychological well-being of the respondent is associated with a significant higher participation in the labour market. The coefficients of the IV regressions are larger than the corresponding ones from OLS and FE, indicating the presence of measurement errors in the mental health variable that bias the coefficients towards zero. Conversely, it seems that in our panel the correlation between the mental health variable and latent individual heterogeneity is associated with an upward bias. Indeed, accounting for correlated individual effects (i.e. using fixed effects) reduces the magnitude of the mental health coefficient.

In the fifth and seventh columns, we perform pooled probit regressions. In the fifth column, mental health status is assumed to be exogenous; in the seventh column, it is substituted by the individual's social support network, which we assume exogenous. The coefficient of interest remains significant across genders. In the sixth and eighth columns, we apply the Mundlak-type specification (as explained in Section 3) to the respective left columns, thus accounting, once again, for correlated individual effects (which is in order, given the strong joint significance of the Mundlak effects). The last column, in particular, presents the specification used by the Semykina and Wooldridge's (2010) estimator.[9] Even if accounting for both endogeneity of the mental health variable and correlated individual effects in the probit specification reduces the magnitude of the psychological well-being coefficients, a stronger social support network (and thus, according to our hypothesis, lower mental distress) remains associated with a significantly higher probability of participation.

To facilitate the comparisons of the results from linear and non-linear models, Tables 1

[8]The equation is exactly identified, therefore the Hansen J statistic is not available. We strongly reject the hypothesis of weak-identification and that the models are underidentified in both samples.

[9]Note that while in the Semykina and Wooldridge's (2010) procedure used to estimate the wage equation we perform different probit estimations, one for each year, here we present the results for the entire period.

and 2 present participation probabilities of two average (male and female) individuals, who differs only with respect to their "Caseness" score (note that the Probit results include the Mundlak effects). Remember that this score is obtained by counting the number of questions in the GHQ-12 to which the individual responds in the worse two categories, and thus ranges from zero to twelve (see Section 4.2). These tables use a cut-off of 4 to divide the respondents into "normals" and "cases": the clinical literature using the GHQ-12 argues that the latter has a significant higher probability of suffering from a psychiatric illness (e.g. Guthrie et al., 1988, Shaw et al., 2000, Moffat et al., 2004, James et al., 2013).

Table 1: Participation Probabilities (Percent), Males

	OLS	FE	2SLS	FE-2SLS	Naive Probit	Instr Probit
Normals	87.2	85.9	90.0	87.4	86.0	84.4
Cases	66.3	74.7	48.0	64.8	64.7	73.6

Table 2: Participation Probabilities (Percent), Females

	OLS	FE	2SLS	FE-2SLS	Naive Probit	Instr Probit
Normals	91.4	89.9	95.8	91.6	90.3	88.7
Cases	76.3	82.7	58.3	74.6	75.4	82.1

The male probit estimates show the probability difference between "normals" and "cases" to vary between 21.3 percentage point when the mental health is considered exogenous and 10.8 percentage points when mental health is considered endogenous. In the female samples, and considering the probit specifications, the probability difference vary between 6.6 percentage points when controlling for endogeneity and 14.9 when we do not.

The effects of the remaining variables are as follows. For both men and women, age turns out to be a significant factor influencing participation in the labour market, with the probability of entering the workforce increasing with age until it reaches a peak and begins to slowdown. The existence of another source of income significantly reduces the individuals' labour market attachment for both sexes. The presence of children in the households has an impact only on females participation, and it is found to be positive for both children younger and older than 4 years old. While one could expect a negative effect on the participation of females of the presence of very young child, the effect here is positive. This may be explained by the need to return to the workforce to provide additional economic support to the household. Having a first or higher degree increases the probability of participation, especially for females. Being white is associated with a significantly higher probability of being employed. The partner characteristics are generally not significant across genders and specifications.

5.2 Wage equation

The results of five of our econometric estimations for our equation of interest are reported separately for men and women in Tables 6 and 7, respectively. The results from the Pooled OLS estimator are presented in the first column and represent a benchmark for the subsequent regressions. The second column shows the within results that account for the two components of the error term.[10] The coefficient obtained using Pooled OLS is higher than the coefficient obtained using FE, suggesting a positive correlation between mental health status and latent individual heterogeneity. In the last three columns, we correct for the assumed endogeneity of the health variables using 2SLS, FE-2SLS, and the Semykina and Wooldridge's (2010) estimator, respectively. As explained above, we use the perceived social support network of the respondent as instrument for the mental health variable (see Section 4.3); however, following Wooldridge (1995), we also include as instruments the exclusion restrictions of the participation equation (see Section 4.4).

We test the rank conditions using an F-test on the joint-significance of the instruments

[10]We do not present the results of the GLS estimation since the Sargan-Hansen statistic on the overidentifying restrictions indicates that the GLS orthogonality conditions are not satisfied in both samples. These are available on request.

in the first stage of the 2SLS and FE-2SLS regressions.[11] We find that the null hypothesis of weak-identification is rejected at any sensible level. Moreover, we strongly reject the hypothesis that the models are underidentified in both samples. Finally, we test for overidentifying restrictions using Hansen's J statistics. For both samples, we strongly reject the null that our instruments are valid in the 2SLS; in the FE-2SLS, conversely, p-values of 0.859 and 0.335 suggest that our set of instruments is appropriate. Semykina (2012) argues that a rejection of the null hypothesis of valid instruments could be a signal of the presence of selection bias. As a further test of the presence of selection bias, Wooldridge (1995) suggests to include the IMRs deriving from the T probit estimations of the participation equation as explanatory variables in the within regression and in the FE-2SLS, and to perform a Wald-test on the joint significance of the IMRs coefficients. If the resulting statistic is greater than the critical value, one should reject the null of no sample selection. As one can see in Table 3, we reject the null in both 2SLS and FE-2SLS only for the female sample. We interpret this as suggesting that, while in the male sample selection bias does not seem to be a problem, the female sample is not randomly selected, thus requiring the use of procedure proposed by Semykina and Wooldridge (2010).

Table 3: Tests on Selection Effects, Males and Females

	FE		FE-2SLS	
	Males	Females	Male	Females
Wald-test	0.63	2.73	2.46	16.53
P-values	0.7292	0.0079	0.9298	0.0207

While good psychological well-being significantly increases participation for both females and males, we find a significantly positive effect on wages in most specifications only for the female sample. This is interesting though considering that females on aver-

[11] Since we use cluster robust standard errors, the relevant test statistics is the so-called "Kleibergen-Paap Wald rk F-test". Since critical values in this case are unknown, we use Stock-Yoko critical values for the i.i.d. case.

age reported worse psychological health in our sample. This is in line with Contoyannis and Rice (2001) who suggested that it may be the case that either males tend to underestimate psychological health relative to females or societies and/or employers favourably discriminate females with regards to psychological health. Whatever the reason, we find that, when accounting for all sources of endogeneity, the elasticity between psychological well-being and hourly wage is equal to 0.154.

To facilitate the comparisons of the results from the different regressions, Tables 4 and 5 present predicted hourly wages in GBP of two average individuals, who differs only with respect to their "Caseness" score. A male in "normal" mental health is predicted to have an hourly wage that is between 0.11£ and 1£ higher than a male more likely to suffer for mental illness. Accounting for correlated individual effects reduce the wage gap, whereas accounting for endogeneity increases it. For females, the wage gap is null when health is considered exogenous, but grows to 1.46£ under the 2SLS estimator. Accounting for correlated individual effects shrinks the gap to 0.17£, but when non random selection into the workforce is additionally considered the wage gap between a "normal" and a "case" female jumps to 1.03£ (or, equivalently, 18.6%).

Table 4: Hourly Wage Predictions (GBP), Males

	OLS	FE	2SLS	FE-2SLS	SW
Normals	8.31	8.07	7.96	8.37	7.88
Cases	7.94	7.96	6.76	7.77	7.41

Table 5: Hourly Wage Predictions (GBP), Females

	OLS	FE	2SLS	FE-2SLS	SW
Normals	6.41	6.40	6.65	6.42	6.57
Cases	6.40	6.44	5.19	6.25	5.54

We now turn our attention to the other independent variables. For both samples, the set of coefficients on the third-degree polynomial of age and experience exhibits the expected signs, and is significant at 1% in all specifications, implying consistency with the quadratic and concave profile of the IHS transformation of average hourly wage. The dummy related to the level of education is significant and positive for females, indicating a rate of return on having a degree or a higher education attainment that ranges from 6% (when accounting for selection) to 23% (in the OLS specification). For males, the coefficient is usually not significant. The strong correlation with women's wages and the fact that coefficients are usually higher with respect to the ones found for males might indicate that women tend to self-select in qualification types in order to show their abilities.

For both males and females, there is a gradient in wages which reflects occupational status and most of the coefficients are significant at 1% level. In general, being a professional is associated with a slightly higher average hourly wage with respects to being a manager, but this could be an indicator that managers can also be compensated with perks which are not accounted for in the hourly wage. For women, being a manual skilled worker has a negligible effect on wage compared with being an unskilled worker while the difference is less marked for men. This may be explained by the fact that, blue collar work is done mostly by men in our samples. For men, working in the private sector increases hourly wage by up to 5% compared to those who work in the public sector. On the contrary, women who work in the private sector earn as much as 7% less than in the public sector. This may be due to weakest gender discrimination in the public sector if compared with the private one.

Men's wages appear to be much more negatively affected by the choice of switching to part-time than women: wages appear to decreases by as much as 77% for men but only by up to 15% for women. However, this result may not be completely informative since for males only 4% of total observations are in part-time occupation, while the proportion increases to 34% for females. An increase in the number of employees at the individual's work place is associated with a strongly significantly but negligibly rise in wages. Having taken any job related training in the previous year is also associated with a significant increase in wages. As expected, unions have a positive impact on wages, and predictably the effect is greater (almost double) for members than non-members still covered by union bargaining and renegotiation. In general, union membership appears to have a larger impact on wages for women than for men, which might be caused by positive selection of women in unions.

Having small children significantly increases hourly wages for both females and males, consistently with Contoyannis and Rice (2001). At least for the females, however, this result may be contaminated by the presence of simultaneity and endogeneity bias for which we do not correct for. The presence of dependent children older than 4 years has a positive and significant effect on the wage for men, while it impacts negatively the wage for females. This may be due to lost opportunities of career advancements during maternal leave, when compared with women with no children, which do not seem to influence males. The marital status does not appear to be significant across genders.

6 Conclusions

In examining the relationship between health on wages for a sample of British employees, Contoyannis and Rice (2001) found decreasing mental health to have a negative impact on wages of employed males. In this paper, we investigate the relationship between self-assessed psychological well-being and labour market outcomes for the entire population, not only for those individuals who are employed. In order to do so, we employ, for the first time in the analysis of the effect of mental health on wages, an estimator proposed by Semykina and Wooldridge (2010) which allows to control for sample selection in a fixed effects model with endogeneity. This means that, unlike Contoyannis and Rice (2001), we are able to address endogeneity, sample selection, and unobserved heterogeneity in a comprehensive framework.

We provide evidences that correcting for non random selection into the workforce is necessary at least for the female sub-sample. Our empirical results show, moreover, that mental distress significantly decreases the probability of participating to the labour market, both for males and females. When investigating the direct effect of psychological well-being on hourly wages, we find it to have a significant and positive effect only for the female sample. As a consequence, our findings suggest that mental health status is important both on the intensive and extensive margins for females, while it only influences males with respects to their participation decision to the labour market.

The measure of psychological well-being that we used in this paper covers various aspects, like feelings of incompetence, anxiety, depression, difficulty in coping, and sleep disturbance. The accuracy of this measure, however, is dependent on individuals providing reliable and accurate responses. It is very likely the case, however, that respondents have a perceived incentive to under-report mental illness, because of the fear of being stigmatised, socially sanctioned, or disgraced (Bharadwaj et al., 2017, Brown et al., 2018). If this is the case, the results that we presented here are likely to be a lower-bound of the true effect of mental distress on labour market outcomes.

Table 6: Wage Equation, Males

	OLS	FE	2SLS	FE-2SLS	SW
Log Mental Health	0.007	0.007	0.207***	-0.025	0.107
	(0.0084)	(0.0077)	(0.0621)	(0.0864)	(0.0886)
Age	0.112***	0.205***	0.120***	0.213***	0.179***
	(0.0104)	(0.0149)	(0.0104)	(0.0150)	(0.0143)
Age square	-0.210***	-0.348***	-0.229***	-0.381***	-0.356***
	(0.0275)	(0.0368)	(0.0278)	(0.0364)	(0.0369)
Age cube	0.001***	0.002***	0.001***	0.002***	0.002***
	(0.0002)	(0.0003)	(0.0002)	(0.0003)	(0.0003)
Has a Degree	0.204***	0.026	0.212***	0.019	-0.005
	(0.0161)	(0.0476)	(0.0162)	(0.0499)	(0.0502)
Kids (0-4 yrs)	0.029***	0.019**	0.032***	0.017*	0.028***
	(0.0093)	(0.0091)	(0.0095)	(0.0097)	(0.0100)
Kids (>4 yrs)	0.039***	0.021*	0.040***	0.022*	0.027**
	(0.0111)	(0.0115)	(0.0119)	(0.0119)	(0.0128)
London	0.164***	-0.079*	0.183***	-0.083	-0.085*
	(0.0216)	(0.0452)	(0.0232)	(0.0509)	(0.0487)
White	0.049**		0.046*		
	(0.0247)		(0.0250)		
Widowed	0.091	0.112	0.097	0.101	0.108
	(0.0727)	(0.0768)	(0.0738)	(0.0718)	(0.0748)
Divorced or Separated	-0.069***	-0.023	-0.044**	-0.020	0.010
	(0.0204)	(0.0228)	(0.0213)	(0.0248)	(0.0257)
Never Married	-0.080***	0.003	-0.072***	-0.002	0.023*
	(0.0125)	(0.0170)	(0.0132)	(0.0176)	(0.0183)
Experience	0.009***	0.007***	0.009***	0.007***	0.010***
	(0.0025)	(0.0024)	(0.0025)	(0.0025)	(0.0025)
Experience square	-0.069***	-0.037*	-0.077***	-0.039**	-0.075***
	(0.0193)	(0.0195)	(0.0200)	(0.0196)	(0.0195)
Experience cube	0.001***	0.001	0.001***	0.001	0.001***
	(0.0004)	(0.0004)	(0.0004)	(0.0004)	(0.0004)
Private Sector	0.051***	0.005	0.052***	0.002	0.049***
	(0.0126)	(0.0180)	(0.0127)	(0.0185)	(0.0126)
Professional	0.486***	0.078***	0.479***	0.080***	0.456***
	(0.0219)	(0.0230)	(0.0222)	(0.0247)	(0.0220)
Manager	0.445***	0.075***	0.446***	0.075***	0.420***
	(0.0137)	(0.0162)	(0.0139)	(0.0174)	(0.0138)

Table 6 Continued: Wage Equation, Males

	OLS	FE	2SLS	FE-2SLS	SW
Skilled Non-Manual	0.200***	0.009	0.203***	0.013	0.190***
	(0.0130)	(0.0170)	(0.0136)	(0.0175)	(0.0135)
Skilled Manual	0.086***	-0.008	0.085***	-0.010	0.085***
	(0.0100)	(0.0109)	(0.0103)	(0.0119)	(0.0101)
Part-Time Job	-0.686***	-0.770***	-0.613***	-0.637***	-0.632***
	(0.0491)	(0.0681)	(0.0484)	(0.0682)	(0.0488)
Number of Employees	0.000***	0.000***	0.000***	0.000***	0.000***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Union at Workplace	0.030***	0.037***	0.040***	0.034***	0.041***
	(0.0114)	(0.0121)	(0.0115)	(0.0127)	(0.0113)
Member of Union	0.076***	0.043***	0.076***	0.051***	0.073***
	(0.0120)	(0.0142)	(0.0120)	(0.0150)	(0.0119)
Job Training (lag)	0.045***	0.000	0.042***	0.002	0.037***
	(0.0078)	(0.0070)	(0.0080)	(0.0074)	(0.0079)
Constant	0.245*	-1.224***	-0.485**		0.583
	(0.1239)	(0.2396)	(0.2357)		(0.4511)
Time (joint significance)	332.63***	2.29**	2,274.62***	16.92**	86.41***
N	26,194	26,194	23,268	20,695	21,530

Cluster robust standard errors are reported in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

White is dropped in Semykina and Wooldridge (2010) because of multicollinearity

Table 7: Wage Equation, Females

	OLS	FE	2SLS	FE-2SLS	SW
Log Mental Health	0.015***	0.001	0.219***	0.043	0.154**
	(0.0055)	(0.0055)	(0.0388)	(0.0618)	(0.0641)
Age	0.139***	0.210***	0.139***	0.215***	0.164***
	(0.0103)	(0.0129)	(0.0109)	(0.0132)	(0.0135)
Age square	-0.299***	-0.413***	-0.293***	-0.413***	-0.348***
	(0.0282)	(0.0326)	(0.0298)	(0.0336)	(0.0360)
Age cube	0.002***	0.003***	0.002***	0.003***	0.003***
	(0.0002)	(0.0003)	(0.0003)	(0.0003)	(0.0003)
Has a Degree	0.230***	0.114***	0.226***	0.120***	0.062**
	(0.0147)	(0.0280)	(0.0147)	(0.0309)	(0.0305)
Kids (0-4 yrs)	0.037***	-0.010	0.043***	-0.000	0.037***
	(0.0096)	(0.0107)	(0.0100)	(0.0113)	(0.0114)
Kids (>4 yrs)	-0.053***	-0.059***	-0.048***	-0.050***	-0.026**
	(0.0098)	(0.0109)	(0.0105)	(0.0120)	(0.0120)
London	0.233***	0.102**	0.244***	0.093**	0.079*
	(0.0176)	(0.0400)	(0.0186)	(0.0448)	(0.0476)
White	0.010		0.023		
	(0.0257)		(0.0254)		
Widowed	-0.070**	0.001	-0.028	0.006	0.067
	(0.0348)	(0.0427)	(0.0363)	(0.0465)	(0.0477)
Divorced or Separated	-0.008	0.015	0.020	0.011	0.029
	(0.0136)	(0.0168)	(0.0147)	(0.0188)	(0.0202)
Never Married	-0.026	-0.046***	-0.006	-0.046***	-0.026*
	(0.0112)	(0.0142)	(0.0118)	(0.0150)	(0.0157)
Experience	0.015***	0.011***	0.016***	0.012***	0.015***
	(0.0026)	(0.0023)	(0.0027)	(0.0026)	(0.0027)
Experience square	-0.104***	-0.077***	-0.106***	-0.087***	-0.100***
	(0.0258)	(0.0208)	(0.0278)	(0.0232)	(0.0271)
Experience cube	0.002***	0.001***	0.002***	0.002***	0.002***
	(0.0006)	(0.0005)	(0.0007)	(0.0005)	(0.0007)
Private Sector	-0.062***	-0.016	-0.067***	-0.013	-0.068***
	(0.0096)	(0.0131)	(0.0098)	(0.0139)	(0.0097)
Professional	0.517***	0.087***	0.512***	0.079**	0.480***
	(0.0291)	(0.0298)	(0.0297)	(0.0314)	(0.0294)
Manager	0.401***	0.101***	0.395***	0.091***	0.379***
	(0.0120)	(0.0153)	(0.0127)	(0.0166)	(0.0126)

Table 7 Continued: Wage Equation, Females

	OLS	FE	2SLS	FE-2SLS	SW
Skilled Non-Manual	0.158***	0.023*	0.161***	0.023	0.149***
	(0.0087)	(0.0135)	(0.0092)	(0.0146)	(0.0092)
Skilled Manual	-0.007	-0.010	-0.012	-0.022	-0.016
	(0.0125)	(0.0146)	(0.0135)	(0.0164)	(0.0125)
Part-Time Job	-0.140***	-0.067***	-0.143***	-0.075***	-0.147***
	(0.0096)	(0.0141)	(0.0100)	(0.0153)	(0.0100)
Number of Employees	0.000***	0.000***	0.000***	0.000**	0.000***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Union at Workplace	0.059***	0.046***	0.053***	0.043***	0.0501***
	(0.0103)	(0.0109)	(0.0106)	(0.0117)	(0.0104)
Member of Union	0.097***	0.055***	0.107***	0.059***	0.107***
	(0.0104)	(0.0130)	(0.0109)	(0.0145)	(0.0101)
Job Training (lag)	0.042***	0.005	0.040***	0.005	0.036***
	(0.0066)	(0.0062)	(0.0071)	(0.0067)	(0.0070)
Constant	-0.078	-1.224***	-0.718***		0.358
	(0.1239)	(0.1953)	(0.1713)		(0.3621)
Time (joint significance)	521.14***	5.17***	3,284.20***	30.46***	
N	27,363	27,363	24,223	21,550	22,976

Cluster robust standard errors are reported in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

White is dropped in Semykina and Wooldridge (2010) because of multicollinearity

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Appendix

Table A1: Stepwise adjustment of samples and average number of waves

	Males			Females			Total
	Obs.	Individ.	Waves	Obs.	Individ.	Waves	Obs.
Complete sample	110,221	15,399	11.71	128,775	16,981	12.05	238,996
Available social network info	50,776	13,405	5,71	60,779	15,357	5.87	111,555
Below retirement age	42,914	11,881	5.52	46,601	12,511	5.62	89,515
Above 16 yrs	42,729	11,828	5.53	46,423	12,457	5.62	89,152
Not retired	40,718	11,463	5.45	45,175	12,256	5.57	85,893
Not in education	37,847	10,521	5.46	41,625	11,093	5.57	79,472
Not in maternity leave	37,847	10,521	5.46	41,200	11,073	5.55	79,044
Not in education	37,847	10,521	5.46	41,625	11,093	5.57	79,475
Not in family care	32,305	9,676	5.14	32,113	9,746	4.98	64,418
Not in other labour force status	31,996	9,586	5.12	31,733	9,644	4.97	63,699
Valid info on other variables	31,413	9,430	5.11	31,273	9,529	4.96	62,686
Of which: Employed	26,670			27,826			54,496
Unemployed	4,743			3,447			8,190

Table A2: Variable Definitions

Variable	Label
IHS of Hourly Wage	ISH transformation of average hourly wage
Participation	1 if did paid work last week
	or if no work last week but has job
Log Mental Health	Log transformation of the inverted Caseness score
Social Support Network	Is there someone who will listen, help in a crisis,
	you can relax with, really appreciate you,
	you can count on to offer comfort
Age	Age at date of interview in years
Age square	Square of age at date of interview /100
Age cube	Cube of age at date of interview /100
Has a Degree	1 if 1st or higher degree
Kids (0-4 yrs)	Number of children in the household aged 0-4
Kids (>4 yrs)	1 for presence of dependent children older than 4
London	1 if living in London
White	1 if white
Widowed	1 if widowed or survive civil partner
Divorced or Separated	1 if divorced, separated, or dissolved/separated
	from civil partner
Never Married	1 if never married
Experience	Spell in current job in years
Experience square	Square of spell in current job /100
Experience cube	Cube of spell in current job /100
Private Sector	1 if employed in Private Sector
Professional	1 if professional
Manager	1 if managerial
Skilled Non-Manual	1 if skilled non-manual
Skilled Manual	1 if skilled manual
Part-Time Job	1 if part-time
Number of Employees	Number of employees at workplace (max 1,000)
	as average of the categories (e.g. "1-2" is rescored as 1.5)
Union at Workplace	1 if covered non-member of union
Member of Union	1 if covered union member
Job Training (lag)	1 if received education or training related to
	current employment in the previous year
IHS of Non-Labour Income	ISH transformation of non-labour income
Partner's Monthly Pay	Spouse or partner's monthly gross pay
Has a Partner	1 if cohabits with lawful spouse or live-in partner
Partner's Age	Co-habitant partner's age at date of interview in years
Partner's Age square	Square of co-habitant partner's age at date of interview /100
Partner's Age cube	Cube of co-habitant partner's age at date of interview /100
Partner's Experience	Co-habitant partner's spell in current job in years
Partner's Experience square	Square of co-habitant partner's spell in current job /100
Partner's Experience cube	Cube of co-habitant partner's spell in current job /100
Partner Has Degree	1 if co-habitant partner has 1st or higher degree

Table A3: Summary Statistics, Males

	Count	Mean	Sd	Min	Max
IHS of Hourly Wage	26,466	2.772	.641	0	6.177
Participation	31,413	.850	.358	0	1
Log Mental Health	31,153	2.958	.507	0	3.180
Social Support Network	31,413	4.638	.976	0	5
Age	31,413	38.599	12.440	16	65
Age square	31,413	16.446	9.969	2.56	42.25
Age cube	31,413	757.297	650.953	40.96	2,746.25
Has a Degree	31,413	.152	.359	0	1
Kids (0-4 yrs)	31,412	.173	.450	0	3
Kids (>4 yrs)	31,413	.211	.408	0	1
London	31,413	.065	.247	0	1
White	31,413	.961	.195	0	1
Widowed	31,413	.006	.079	0	1
Divorced or Separated	31,413	.055	.228	0	1
Never Married	31,413	.239	.427	0	1
Experience	26,718	4.906	6.557	0	50
Experience square	26,718	.671	1.716	0	25
Experience cube	26,718	13.559	53.975	0	1,250
Private Sector	26,466	.771	.420	0	1
Professional	26,466	.0723	.259	0	1
Manager	26,466	.316	.465	0	1
Skilled Non-Manual	31,413	.114	.317	0	1
Skilled Manual	31,413	.252	.434	0	1
Part-Time Job	26,670	.044	.205	0	1
Number of Employees	26,587	249.984	328.893	1.5	1,000
Union at Workplace	26,451	.477	.499	0	1
Member of Union	26,451	.313	.464	0	1
Job Training (lag)	29,559	.300	.458	0	1
IHS of Non-Labour Income	31,413	2.721	2.744	0	10.857
Has a Partner	31,413	.225	.418	0	1
Partner's Monthly Pay	15,347	1,021,681	826.847	0	20,558.57
Partner's Age	7,079	44.603	18.716	15	96
Partner's Age square	7,079	23.340	18.450	2.25	92.16
Partner's Age cube	7,079	1382.06	1549.483	33.75	8,847.36
Partner Has Degree	7,079	.113	.316	0	1
Partner's Experience	3,771	4.378	6.045	0	60
Partner's Experience square	3,771	.557	1.616	0	36
Partner's Experience cube	3,771	11.095	58.821	0	2,160

Statistics for partner's variables are conditional on non-missing data.

Table A4: Summary Statistics, Females

	Count	Mean	Sd	Min	Max
IHS of Hourly Wage	27,659	2.556	.602	0	5.705
Participation	31,273	.890	.313	0	1
Log Mental Health	31,039	2.863	.628	0	3.180
Social Support Network	31,273	4.802	.723	0	5
Age	31,273	38.180	11.510	16	60
Age square	31,273	15.902	8.896	2.56	36
Age cube	31,273	708.419	555.398	40.96	2,160
Has a Degree	31,273	.150	.357	0	1
Kids (0-4 yrs)	31,273	.126	.375	0	4
Kids (>4 yrs)	31,273	.266	.442	0	1
London	31,273	.068	.251	0	1
White	31,273	.964	.186	0	1
Widowed	31,273	.016	.127	0	1
Divorced or Separated	31,273	.108	.306	0	1
Never Married	31,273	.195	.396	0	1
Experience	27,915	4.187	5.419	0	47
Experience square	27,915	.469	1.176	0	22.09
Experience cube	27,915	7.761	30.909	0	1,038.23
Private Sector	27,659	.574	.494	0	1
Professional	27,659	.030	.171	0	1
Manager	27,659	.324	.468	0	1
Skilled Non-Manual	31,273	.324	.468	0	1
Skilled Manual	31,273	.073	.260	0	1
Part-Time Job	27,826	.340	.474	0	1
Number of Employees	27,763	215.606	321.857	1.5	1,000
Union at Workplace	27,629	.518	.500	0	1
Member of Union	27,629	.322	.467	0	1
Job Training (lag)	30,253	.324	.468	0	1
IHS of Non-Labour Income	31,273	3.727	2.660	0	10.446
Has a Partner	31,273	.231	.468	0	1
Partner's Monthly Pay	16,331	1796.408	1,269.424	0	31,333.33
Partner's Age	7,238	45.339	18.635	15	101
Partner's Age square	7,238	24.025	18.488	.81	102.01
Partner's Age cube	7,238	1,427.234	1,558.757	33.75	10,303.01
Partner Has Degree	7,238	.113	.317	0	1
Partner's Experience	3,831	4.614	6.222	0	45
Partner's Experience square	3,831	.600	1.546	0	20.25
Partner's Experience cube	3,831	11.550	45.958	0	911.25

Statistics for partner's variables are conditional on non-missing data.

Table A5: Participation Equation, Males

	OLS	FE	2SLS	FE-2SLS	Naive probit	+ Mundlak	Probit	+ Mundlak
Log Mental Health	0.124***	0.061***	0.311***	0.070*	0.809***	0.595***		
	(0.0053)	(0.0052)	(0.0315)	(0.0362)	(0.0444)	(0.0533)		
Social Support Network							0.178***	0.053*
							(0.0206)	(0.0275)
Age	0.037***	0.027***	0.035***	0.027***	0.462***	0.355***	0.424***	0.312***
	(0.0061)	(0.0078)	(0.0062)	(0.0078)	(0.0550)	(0.0852)	(0.0539)	(0.0827)
Age square	-0.073***	-0.065***	-0.066***	-0.065***	-0.984***	-0.591***	-0.909***	-0.502**
	(0.0160)	(0.0180)	(0.0163)	(0.0180)	(0.1422)	(0.2223)	(0.1397)	(0.2156)
Age cube	0.000***	0.000***	0.000**	0.000***	0.006***	0.003*	0.006***	0.003
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0012)	(0.0018)	(0.0011)	(0.0018)
Has a Degree	0.113***	-0.019	0.114***	-0.019	1.234***	-0.485	1.183***	-0.411
	(0.0062)	(0.0209)	(0.0067)	(0.0209)	(0.1104)	(0.3996)	(0.1094)	(0.4190)
Kids (0-4 yrs)	-0.007	-0.004	-0.008	-0.004	-0.013	-0.019	0.009	-0.025
	(0.0054)	(0.0049)	(0.0055)	(0.0049)	(0.0683)	(0.0897)	(0.0676)	(0.0891)
Kids (>4 yrs)	-0.001	0.003	0.003	0.003	0.110	0.119	0.084	0.093
	(0.0063)	(0.0061)	(0.0066)	(0.0061)	(0.0803)	(0.1102)	(0.0781)	(0.1061)
London	0.010	0.010	0.015	0.011	-0.020	0.113	-0.020	0.085
	(0.0123)	(0.0211)	(0.0129)	(0.0212)	(0.1294)	(0.3234)	(0.1279)	(0.3252)
Widowed	0.044	0.082***	0.055	0.082***	0.335	0.659**	0.227	0.548*
	(0.0403)	(0.0296)	(0.0397)	(0.0296)	(0.2202)	(0.2993)	(0.2147)	(0.2896)
Divorced or Separated	-0.059***	0.010	-0.037**	0.012	-0.221**	0.224	-0.292***	0.106
	(0.0138)	(0.0120)	(0.0145)	(0.0128)	(0.1082)	(0.1671)	(0.1054)	(0.1610)
Never Married	-0.040***	-0.012	-0.038***	-0.012	-0.351***	-0.180	-0.337***	-0.214
	(0.0098)	(0.0094)	(0.0100)	(0.0095)	(0.0913)	(0.1492)	(0.0926)	(0.1535)
White	0.049***		0.043***		0.564***	0.595***	0.581***	0.634***
	(0.0136)		(0.0139)		(0.1285)	(0.1524)	(0.1277)	(0.1503)

Table A5 Continued: Participation Equation, Males

	OLS	FE	2SLS	FE-2SLS	Naive probit	+ Mundlak	Probit	+ Mundlak
IHS of Non-Labour Income	-0.063***	-0.036***	-0.059***	-0.036***	-0.505***	-0.397***	-0.507***	-0.395***
	(0.0013)	(0.0014)	(0.0015)	(0.0014)	(0.0170)	(0.0178)	(0.0165)	(0.0173)
Has a Partner	0.023	0.012	0.068	0.014	-1.240	-1.637	-1.323	-1.847
	(0.0906)	(0.0687)	(0.0957)	(0.0687)	(1.3766)	(1.3754)	(1.3261)	(1.3335)
Partner's Monthly Pay	0.000***	0.000*	0.000***	0.000	0.001***	0.000***	0.001***	0.000***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Partner's Age	0.002	-0.001	-0.002	-0.001	0.137	0.145	0.148	0.162
	(0.0075)	(0.0055)	(0.0079)	(0.0055)	(0.1122)	(0.1106)	(0.1082)	(0.1075)
Partner's Age square	-0.006	0.001	0.006	0.001	-0.366	-0.390	-0.405	-0.443*
	(0.0191)	(0.0134)	(0.0200)	(0.0134)	(0.2834)	(0.2747)	(0.2742)	(0.2681)
Partner's Age cube	0.000	0.000	-0.000	0.000	0.003	0.003	0.004	0.004*
	(0.0002)	(0.0001)	(0.0002)	(0.0001)	(0.0023)	(0.0022)	(0.0022)	(0.0021)
Partner's Experience	-0.003	-0.003	-0.002	-0.003	-0.053	-0.057	-0.052	-0.060
	(0.0028)	(0.0022)	(0.0030)	(0.0022)	(0.0369)	(0.0412)	(0.0355)	(0.0402)
Partner's Experience square	0.021	0.018	0.017	0.018	0.418	0.424	0.390	0.423
	(0.0204)	(0.0154)	(0.0219)	(0.0153)	(0.2578)	(0.2867)	(0.2503)	(0.2843)
Partner's Experience cube	-0.000	-0.000	-0.000	-0.000	-0.008*	-0.007*	-0.007*	-0.007
	(0.0004)	(0.0002)	(0.0004)	(0.0002)	(0.0042)	(0.0043)	(0.0041)	(0.0044)
Partner Has a Degree	0.004	-0.009	0.005	-0.009	-0.070	-0.148	-0.085	-0.179
	(0.0124)	(0.0101)	(0.0129)	(0.0101)	(0.1597)	(0.1733)	(0.1547)	(0.1680)
Constant	0.037	0.436***	-0.528***		-5.972***	-9.624***	-3.914***	-6.897***
	(0.0780)	(0.1304)	(0.1204)		(0.6900)	(1.0702)	(0.6616)	(1.0477)
Time (joint significance)	10.18***	3.20***	59.52***	22.44***	21.79***	6.10	17.26**	5.86
Mundlak (joint significance)						399.82***		400.84***
N	27,866	27,866	27,866	24,883	27,866	27,866	28,104	28,104

Cluster robust standard errors are reported in parentheses; * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table A6: Participation Equation, Females

	OLS	FE	2SLS	FE-2SLS	Naive probit	+ Mundlak	Probit	+ Mundlak
Log Mental Health	0.092***	0.040***	0.271***	0.065**	0.577***	0.375***		
	(0.0045)	(0.0039)	(0.0248)	(0.0319)	(0.0302)	(0.0352)		
Social Support Network							0.222***	0.056*
							(0.0233)	(0.0289)
Age	0.080***	0.041***	0.076***	0.041***	0.820***	0.583***	0.806***	0.593***
	(0.0069)	(0.0088)	(0.0072)	(0.0087)	(0.0707)	(0.1031)	(0.0708)	(0.1021)
Age square	-0.190***	-0.098***	-0.176***	-0.096***	-1.933***	-1.285***	-1.910***	-1.325***
	(0.0187)	(0.0218)	(0.0195)	(0.0218)	(0.1888)	(0.2737)	(0.1887)	(0.2702)
Age cube	0.001***	0.001***	0.001***	0.001***	0.014***	0.009***	0.014***	0.009***
	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0016)	(0.0023)	(0.0016)	(0.0023)
Has a Degree	0.061***	0.027*	0.058***	0.029*	0.867***	0.536*	0.860***	0.492*
	(0.0056)	(0.0153)	(0.0062)	(0.0155)	(0.1016)	(0.3168)	(0.1013)	(0.2982)
Kids (0-4 yrs)	0.099***	0.044***	0.087***	0.044***	0.507***	0.387***	0.542***	0.396***
	(0.0075)	(0.0058)	(0.0080)	(0.0058)	(0.0753)	(0.0963)	(0.0755)	(0.0953)
Kids (>4 yrs)	0.162***	0.065***	0.146***	0.065***	0.901***	0.631***	0.917***	0.638***
	(0.0078)	(0.0062)	(0.0083)	(0.0062)	(0.0667)	(0.0872)	(0.0656)	(0.0854)
London	0.007	0.011	0.006	0.011	0.086	0.265	0.076	0.266
	(0.0099)	(0.0225)	(0.0104)	(0.0224)	(0.1253)	(0.3485)	(0.1250)	(0.3576)
Widowed	0.148***	0.024	0.168***	0.033	0.711***	0.194	0.573***	-0.033
	(0.0231)	(0.0249)	(0.0235)	(0.0276)	(0.1886)	(0.3072)	(0.1875)	(0.3022)
Divorced or Separated	-0.018	-0.000	0.010	0.003	-0.068	-0.003	-0.158*	-0.105
	(0.0109)	(0.0100)	(0.0116)	(0.0109)	(0.0872)	(0.1296)	(0.0875)	(0.1290)
Never Married	-0.024***	-0.003	-0.022***	-0.002	-0.249***	-0.153	-0.247***	-0.172
	(0.0082)	(0.0088)	(0.0084)	(0.0091)	(0.0866)	(0.1308)	(0.0873)	(0.1316)
White	0.039***		0.039***		0.587***	0.715***	0.539***	0.640***
	(0.0140)		(0.0145)		(0.1463)	(0.1661)	(0.1470)	(0.1667)

Table A6 Continued: Participation Equation, Females

	OLS	FE	2SLS	FE-2SLS	Naive probit	+ Mundlak	Probit	+ Mundlak
IHS of Non-Labour Income	-0.053***	-0.027***	-0.048***	-0.027***	-0.429***	-0.307***	-0.433***	-0.307***
	(0.0014)	(0.0014)	(0.0016)	(0.0014)	(0.0169)	(0.0179)	(0.0168)	(0.0179)
Has a Partner	-0.009	0.004	0.046	0.006	0.128	0.271	-0.042	0.095
	(0.0728)	(0.0619)	(0.0861)	(0.0631)	(1.1299)	(1.1690)	(1.0901)	(1.1276)
Partner's Monthly Pay	0.000***	0.000	0.000***	0.000	0.000***	-0.000	0.000***	0.000
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Partner's Age	0.003	-0.001	-0.002	-0.002	-0.009	-0.041	0.005	-0.028
	(0.0061)	(0.0052)	(0.0072)	(0.0053)	(0.0927)	(0.0957)	(0.0892)	(0.0923)
Partner's Age square	-0.002	0.006	0.008	0.006	0.087	0.141	0.050	0.107
	(0.0155)	(0.0132)	(0.0183)	(0.0135)	(0.2289)	(0.2358)	(0.2196)	(0.2277)
Partner's Age cube	-0.000	-0.000	-0.000	-0.000	-0.001	-0.001	-0.001	-0.001
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0018)	(0.0018)	(0.0017)	(0.0018)
Partner's Experience	-0.002	0.003	-0.004	0.002	0.012	0.055	0.013	0.052
	(0.0027)	(0.0025)	(0.0030)	(0.0025)	(0.0472)	(0.0498)	(0.0460)	(0.0483)
Partner's Experience square	0.003	-0.030	0.015	-0.029	-0.305	-0.717*	-0.303	-0.660
	(0.0222)	(0.0219)	(0.0245)	(0.0220)	(0.4069)	(0.4308)	(0.3956)	(0.4199)
Partner's Experience cube	0.000	0.001	-0.000	0.001	0.008	0.018*	0.009	0.017*
	(0.0004)	(0.0005)	(0.0005)	(0.0005)	(0.0089)	(0.0095)	(0.0087)	(0.0093)
Partner Has Degree	-0.014	-0.007	-0.012	-0.007	-0.328**	-0.320*	-0.338**	-0.302*
	(0.0117)	(0.0086)	(0.0128)	(0.0087)	(0.1665)	(0.1717)	(0.1678)	(0.1702)
Constant	-0.313***	0.359***	-0.814***		-9.027***	-15.847***	-8.165***	-14.718***
	(0.0842)	(0.1341)	(0.1087)		(0.8266)	(1.3051)	(0.8237)	(1.2911)
Time (joint significance)	8.98***	1.47	52.16***	9.82	22.42***	13.53*	14.88**	13.04*
Mundlak (joint significance)						360.49***		359.47***
N	27,648	27,648	27,648	24,693	27,648	27,648	27,865	27,865

Cluster robust standard errors are reported in parentheses; * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$