# A Longitudinal analysis of mental health mobility in Britain

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**Summary**

This paper is concerned with quantifying the level of mental health mobility in the British Household Panel Survey (BHPS). We investigate whether the extent of mobility is different across categories of socio-economic groups such as income quintiles, educational attainment and social class group. Our measure of mental health is the 12-item version of the General Health Questionnaire (GHQ) that serves as a self-administered screening test aimed at detecting psychiatric disorders among respondents in community and non-psychiatric settings. Using eleven waves of the BHPS and a variety of methods we show there is much mobility in mental health from one wave to the next. Further the extent of mobility varies across socio-economic categories with greatest persistence observed in more disadvantaged groups. In general, these groups suffer poorer mental health and experience more prolonged periods of ill-health.

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## Introduction

Mental health problems are a leading cause of morbidity and disability, bringing distress to individuals and families and constituting a substantial and costly public health burden [1,2]. In combating mental illness, the UK National Health Service is following a combined strategy of mental health promotion targeted at groups that are deemed most at risk of developing mental illness, e.g. socially disadvanteged groups and individuals experiencing a major life crisis such as bereavement or divorce, and curative services targeted at patients already suffering from mental ill-health [3]. However, evidence on the benefits of both prevention and curative services is limited. There exist few conclusive systematic reviews on the effectiveness of mental health interventions whilst the vast majority of prevention and mental health promotion programmes have not, to date, been subjected to systematic review [4]. Despite the lack of evidence on the effectiveness and cost-effectiveness of mental health programme policies such as community support mental health teams, support groups for identifiable individuals at risk, pre-school education for deprived children, and action on smoking, alcohol and drug abuse have been implemented in the UK [1].

Mental health prevention programmes tend to adopt a broad-brush approach to targeting individuals most likely to be at risk of developing mental health problems. Accordingly, whilst capturing individuals at high risk of mental illness they are also directed at individuals who – although a member of the same perceived risk group – are at a substantially lower risk of developing subsequent mental health problems. On grounds of both equity and efficiency mental health prevention programmes may best be targeted at individuals who are most at risk of developing mental health problems and who suffer from prolonged periods of ill-health. The problem is identifying socio-economic groups most likely to develop these characteristics.

Research into the extent and nature of inequalities in health have, to date, tended to rely on cross-sectional observations of the level of observed health within socio-economic groups of interest. Cross-sectional information can, at best, provide a snap-shot of the overall distribution of health at any particular point in time with respect to factors of interest such as income, employment status or social class [5,6]. What they cannot provide is evidence on the intertemporal persistence of mental health problems across different socio-economic groups.

The paper is concerned with identifying the level of reported mental ill-health and quantifying how mobile over time individuals are within the overall distribution of mental health. Observed mobility in health outcome is then compared across socio-economic groups. We use data from the British Household Panel Survey (BHPS). The mental health measure is derived from a self-administered screening test aimed at detecting psychiatric disorders among respondents. The extent of mobility in our sample is estimated using two comparative measures. The first partitions unobserved variability in health states from an error components model into transitory and permanent components and uses the proportion of total variability attributed to the permanent component as a measure of mobility. The smaller this proportion, the greater the extent of health mobility. The second measure of mobility is based on he estimated coefficient on lagged health status from a dynamic regression model. This is estimated via OLS. The smaller the coefficient, the greater the extent of health mobility. We then decompose our estimates of mobility into components attributable to state dependence and unobserved heterogeneity.

The paper is organized as follows. The next section providers information on the British Household Panel Survey (BHPS), our sample, the measure of mental health and the explanatory variables used. This is followed by descriptive evidence on the extent of mobility in our sample using correlation and transition matrices. We then describe more formal methods and empirical models used to determine health mobility. Results are then reported separately for men and women and broken down by age, socio-economic group and level of health status. A discussion of the results and conclusion is provided in a final section.

## Data

### The British Household Panel Survey

We use 11 waves of data from the British Household Panel Survey (BHPS). 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 (see Taylor [7] for a detailed documentation of the BHPS). The first wave of the survey was conducted between September 1990 and April 1991. 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 in Britain. The sample for waves two onwards consists of all eligible adults in all households where there is at least one interview at wave one. We use data on individuals who were questioned at wave one and who provided valid responses to the variables described below in at least the first wave. Our working sample consists of 9803 individuals, 4549 men and 5254 women.

## Dependent variable

Our measure of mental health is the 12-item version of the General Health Questionnaire (GHQ) developed by Goldberg [8]. The GHQ is a self-administered screening test aimed at detecting psychiatric disorders that require clinical attention among respondents in community and non-psychiatric clinical settings. The GHQ can detect disorders of a temporary nature such as depression and anxiety, but also permanent conditions such as schizophrenia and psychotic depression. The main advantage of the GHQ is that it does not require a subjective assessment by a specialised clinician. The BHPS uses a 12-item version of the GHQ based on answers to questions on 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. Respondents rate each item on a four point scale (ranging from 0 to 3, 0 being the best score). The questions are formulated in a way such that respondents are more inclined to take their own previous health states as a comparison when responding to the questions. A Likert scale [9] is used to form an overall score (GHQ) for each respondent based on summing across the item specific responses. This provides a mental health variables ranging from 0 (least distressed) to 36 (most distressed). The predictive validity and content validity of the GHQ are good in comparison to other well-known scaling tests of mental illness [10]. The GHQ also performs well in reliability tests [10], and has proven to be robust against retest effects [11].

## Explanatory variables

Our income variable is a measure of household income constructed from information on the annual labour and non-labour income of each member of the household. To allow for the effects of household size and composition, household income is equivalised using the McClements scale [7]. It is also deflated to 1991 prices using the retail price index. Two household income variables are constructed. First, we use current annual household income (LNINC) and secondly, we use the individual specific mean of annual household income (MLNINC). Both of these variables are transformed to natural logarithms to allow for concavity in the health-income relationship. We refer to the transformed variables as transitory and permanent income respectively. Other variables included in the analysis are marital status (MARCOUP, WIDOWED, NVRMAR, DIVSEP), the highest educational qualification attained during the sampling period (DEGHDEG, HNDALEV, OCSE, NOQUAL), an indicator of ethnic origin (OTHETH), the number of persons in the household (HHSIZE) and the number of children in the household (NCH04, NCH511, NCH1218). Occupational social class is derived from information on the respondents present or pre-retirement (if available) registrar general's social class, and from the respondents job status. Around 30% of respondents do not belong to a social classification because they are either retired, unemployed, studying, occupied with family care, disabled or in government training. The full list of variables used are professional (PROF), managerial or technical (MANTECH), skilled non-manual (SKNONM), skilled manual (SKLMANAR), partly- or unskilled (UNPSKL), unemployed (UNEMP), retired (RETIRED), family care (FAMCARE), and other social class (SCOTHER). We allow for a flexible relationship between the GHQ score and age by specifying a cubic polynomial in age (AGE, $AGE^2$, and $AGE^3$). A vector of time dummies is included to capture aggregate health shocks, time-varying reporting changes, and any effects of age that are not captured by the polynomial. Table 1 provides variable names and definitions.

**Insert Table 1 here**

Descriptive statistics for the full sample and for men and women broken down by health status are provided in Table 2. In general, our sample males report better psychological health (lower GHQ scores) than women. Also, men are slightly younger and belong to households with higher income. They are less likely to be widowed or divorced/separated, have higher academic qualifications and are more likely to be employed in professional, managerial and skilled manual professions and less likely to be employed in skilled non-manual professions. Stratifying the sample by healthy and unhealthy reveals the following (see footnote to Table 1 for definitions of healthy and unhealthy individuals). Healthy individuals tend to be associated with higher incomes, are slightly younger, are more likely to be of white ethnic origin, are less likely to be widowed or divorced/separated, have higher academic qualifications and belong to a professional, managerial or skilled social class group compared to their unhealthy counterparts.

**Insert Table 2 here**

The focus of attention in this paper is observed mobility in mental health across socio-economic groups. A simple description of mobility is presented for men and women in Table 3. The correlations in GHQ scores across the 11 waves of data show a clear pattern. As expected, waves closer together have, in general, higher correlations than waves further apart. Accordingly the highest correlations occur in the cells adjacent to the lead diagonal. These correlations then show a tendency to drop off as one moves further away from the lead diagonal until a degree of levelling out occurs. The off-diagonal correlations vary between 0.315 and 0.556 for men and 0.302 and 0.525 for women. These correlations show that although health outcomes are more similar the closer the reporting period, the absolute size of the correlations suggest that there exists considerable mobility in GHQ scores over time. For example, all correlations off the lead diagonal are much smaller than one (one indicating an absence of mobility) and less than a fifth are over 0.5. However the non-zero correlation at the extremes suggests that this mobility operates around some underlying persistence in individual health trajectories.

**Insert Table 3 here**

The degree of mobility in health outcomes can also be assessed descriptively using a transition matrix. This is a common approach adopted in the early literature on earning and income mobility, see for example Shorrocks [12]. Transition matrices for men and women are presented in Table 4. Here the rows indicate previous health state while the columns indicate the current state. To represent the GHQ scores in this manner, the distribution at time *t* was first partitioned into quintiles. For example, the elements of the first row provide information on the conditional distribution of GHQ quintile at time *t,* given an individuals' GHQ score fell within the first quintile at time *t-1*. Mobility is again observable by considering the relative magnitudes of the diagonal elements and those close to them compared to those far from the diagonal. For example, of men categorised into the 1st quintile (the healthiest) of the distribution of GHQ scores in period *t,* approximately 30% move two quintiles or more in the next period. Similarly for men categorised into the 5th quintile (the unhealthiest) in period *t,* almost 34% move two or more quintiles in the next period. Of men categorised into the middle quintile in period *t,* only 39% remain in the same quintile in the next period. Similar observations are revealed for women. Although, individuals are more likely to remain close to their initial state than move far away from it, the data again reveal considerable mobility in health outcomes over time. Note that caution is advised here as the choice of cut-point used for defining the groups of the transition matrix is largely arbitrary and the size of such groups will, to a degree, influence the level of mobility or persistence interpreted from the data.

**Insert Table 4 here**

## Models and estimation methods

The literature on earnings and income dynamics exploits the panel aspect of survey data by specifying and estimating panel data random effects models to obtain measures of mobility. In these models estimates of variance components derived from random effects specifications provide a useful means of summarizing mobility or persistence in outcomes which can be compared across sub-samples. More latterly, the literature has used the estimated coefficient on the lag of the dependent variable used as an additional regressor in a dynamic model as an appropriate measure of mobility. We adopt similar approaches to estimate mental health mobility in the BHPS sample. In addition we decompose our mobility estimates into terms due to state dependence (the direct impact previous period's health has on current health) and individual unobserved heterogeneity.

## Variance components models

We specify random effects variance component models to estimate the extent of mental health mobility in GHQ scores. These models were first used in this context to estimate income dynamics [13], and since then many variations on this basic approach have appeared in the literature (for an overview of models used for the analysis of income dynamics see Bane [14], Duncan [15] and Stevens [16]). We specify the following empirical model:

$$h_{it} = X_{it}'\beta + Z_i'\gamma + \eta_i + \varepsilon_{it}, \qquad i = 1,2,\ldots,N; t = 1,2,\ldots T_i \tag{1}$$

where $h_{it}$ is the GHQ score for the *i-th* individual at time *t*. $X_{it}$ represents a vector of time-varying explanatory variables and $Z_i$ a vector of time-invariant explanatory variables, assumed to influence $h_{it}$ but to be uncorrelated with the error term, $\mu_i + \varepsilon_{it}$. The total error is composed of $\mu_i$, an individual specific and time-invariant error and $\varepsilon_{it}$, the usual idiosyncratic error component. $\beta$ and $\gamma$ are conformably dimensioned vectors of parameters to be estimated.

Consistent estimation of the above model assumes orthogonality between the unobserved individual specific effect, $\eta_i$ and the set of regressors. To allow for potential correlation between $\eta_i$ and the set of time-varying regressors, $X_{it}$ we parameterize the individual effect to obtain a correlated random effects model [17,18]. The null hypothesis that $X_{it}$ are uncorrelated with the individual effect $\eta_i$ can by tested using the procedure suggested by Hausman [19].

We use the estimates of $\sigma_\eta^2$ and $\sigma_\varepsilon^2$ as a means of determining the degree of mental health mobility (or conversely persistence) in our sample. Total variation in health outcomes conditional on the set of regressors, $X_{it}$ and $Z_i$ and the parameterization of the unobserved individual effect is given by:

$$\mathrm{var}(\eta_i + \varepsilon_{it}) = \sigma_\eta^2 + \sigma_\varepsilon^2 \tag{2}$$

Since the idiosyncratic errors, $\varepsilon_{it}$, are assumed to be independent the covariance between two observations on the same individual is:

$$\mathrm{cov}\left(\eta_i + \varepsilon_{it_1}, \eta_i + \varepsilon_{it_2}\right) = \mathrm{cov}\left(\eta_i, \eta_i\right) = \sigma_\eta^2 \qquad (3)$$

Hence, the correlation between two such observations is given by:

$$\rho = \frac{\sigma_\eta^2}{\sigma_\eta^2 + \sigma_\varepsilon^2} \qquad (4)$$

This is the intra-unit correlation coefficient that represents the correlation of GHQ scores across periods of observation. Should $\sigma_\eta^2$ be large in comparison to the total error variance, $\sigma_\eta^2 + \sigma_\varepsilon^2$, resulting in a relatively large value of $\rho$ then individuals are said to experience relatively high persistence and low mobility in health outcomes. Conversely, if the majority of unexplained variability is attributable to $\sigma_\varepsilon^2$ then individuals experience relatively high random fluctuations resulting in high mobility and low persistence in health outcomes. Models were estimated by maximum likelihood using STATA [20].

## Dynamic Error Components Models

We augment the set of regressors in model (1) to include the previous period's GHQ score in order to estimate directly the impact of previous health state on current health outcomes (Contoyannis, Jones and Rice [21,22] estimate similar models with discrete health outcome variables). The general form of this dynamic model can be written as:

$$h_{it} = \lambda h_{it-1} + X'_{it}\beta + Z'_i\gamma + \nu_{it}, \qquad i = 1,2,\ldots,N;\ t = 1,2,\ldots T_i \qquad (5)$$

where $h_{it}$, $X_{it}$, $Z_i$, are defined as before.

Our approach to estimation is as follows: first we estimate (5) by OLS. OLS estimation of $\lambda$ is biased upwards if there is serial correlation in the error, $\nu_{it}$, due to an unobserved individual effect. Without conditioning on unobserved individual heterogeneity, OLS estimation of $\lambda$ reflects both state dependence and the correlation between $h_{it-1}$ and unobserved heterogeneity. This composite parameter estimate forms our second measure of mobility (see for example Jarvis and Jenkins, [23]). A coefficient close to zero provides evidence of high mobility since current health will not be a function of previous periods health (conditional on $X_{it}$, and $Z_i$). Accordingly, conditional on $X_{it}$, and $Z_i$, health outcomes fluctuate in a non-deterministic and random manner over time. Conversely, if the estimate of $\lambda$ is positive and large, individuals are characterised by relatively low health mobility. A negative coefficient would indicate cyclical fluctuations in health outcomes over time.

Secondly, we decompose our estimate of mobility into components due to state dependence and individual heterogeneity. We do this in two ways. For both we initially assume random effects for the total error such that $v_{it} = \eta_i + \varepsilon_{it}$. Our first approach is to first-difference the model to remove the individual unobserved effect. However, this also removes the time-invariant variables, $Z_i$, and induces a correlation between the first differenced lagged health variable $(h_{it-1} - h_{it-2})$ and the first-differenced idiosyncratic error component, $(\varepsilon_{it} - \varepsilon_{it-1})$. The model in first-differences can be estimated using a Generalised Method of Moments (GMM) instrumental variables estimator derived by Arellano and Bond [24]. The estimator employs lagged levels of the dependent variable as instruments for the first-differenced lagged dependent variable to identify $\lambda$. Arellano and Bond exploit the time dimension of the panel by extending the set of instruments at any particular time $t$ by using additional moment conditions when they become available. For example, $h_{i1}$ is a suitable instrument for the first differenced lagged health variable $(h_{i2} - h_{i1})$ since it is not correlated with the corresponding first-differenced idiosyncratic error term, $(\varepsilon_{i3} - \varepsilon_{i2})$. However, both $h_{i1}$ and $h_{i2}$ are suitable instruments for the first differenced lagged variable, $(h_{i3} - h_{i2})$. Similarly, $h_{i1}$, $h_{i2}$ and $h_{i3}$ are suitable instruments for the first differenced lagged variable, $(\varepsilon_{i4} - \varepsilon_{i3})$. Accordingly, the number of instruments available increases with the time dimension of the panel. The methodology assumes that there is no second-order autocorrelation in the first-differenced idiosyncratic errors. Estimation of this model together with a test for second-order autocorrelation and the Sargan test of over-identifying restrictions for instrument validity [24] was performed using STATA [20].

Estimating the model by GMM-IV after taking first differences allows us to identify the state dependence parameter, $\lambda$, but does not provide us with an estimate of the contribution of individual heterogeneity. Wooldridge ([25], p412) suggests a method of estimating (5) without transforming to first-differences or deviations from group means that allows us to investigate the separate roles of heterogeneity and state dependence. His approach consists of modelling the distribution of the unobserved effect conditional on the initial value of the dependent variable, $h_{i0}$, and any exogenous explanatory variables. This conditional maximum likelihood (CMLE) approach results in a likelihood function based on the joint distribution of the observations conditional on initial health. Parameterizing the distribution of the unobserved effects leads to a likelihood function that is easily maximised using pre-programmed commands with standard software (e.g. STATA). However it should be noted that the CMLE approach specifies a complete model for the unobserved effects and may therefore be sensitive to misspecification. For an application of this method to non-linear dynamic panel data models see Contoyannis, Jones and Rice [22].

We implement this approach by parameterizing the distribution of the individual effects as:

$$\eta_i = \alpha + \alpha_1 h_{i0} + \alpha_2' \overline{X}_i + u_i \qquad (6)$$

where $\overline{X}_i$ is the average over the sample period of the observations on the exogenous variables. $u_i$ is assumed to be distributed $\mathrm{N}(0, \sigma_u^2)$ and independent of the X variables, the initial condition, and the idiosyncratic error term, $\varepsilon_{it}$. Substituting (6) into (5) gives a model that has a random effects structure, with the regressors at time *t* augmented to include $h_{i0}$ and $\overline{X}_i$. Estimates of $\alpha_1$ are also of interest as they are informative about the relationship between the individual effect and initial health.

## Results

The results for the various model specifications outlined above are reported in this section. Models for men and women are presented separately throughout.

### Model Specification

Tables 5 and 6 present coefficient estimates for the variance components maximum likelihood estimation, OLS, GMM IV in first-difference form and the conditional maximum likelihood estimation. The Hausman test for fixed versus random effects specification fails to reject the null hypothesis of no correlation between the time-varying regressors and the unobserved individual effect once the individual effect has been parameterised using the within-individual means of the regressors; men: $\chi^2_{30} = 43.2, p = .06$, women: $\chi^2_{30} = 21.7, p = .87$. A RESET test of misspecification applied to the models suggests that for both men and women, the CMLE model is the better specified; men: $\chi^2_3 = 7.5, p = .06$, women: $\chi^2_3 = 1.88, p = .60$. Other models tested failed quite dramatically except for the variance components MLE for women; $\chi^2_3 = 6.28, p = .10$. The superiority of the CMLE specification compared to the variance components MLE specification is also evident from the change in log-likelihood values.

**Insert Table 5 here**

In general, individuals who are widowed or divorced/separated exhibit worse mental health than the baseline category of married/cohabiting. The effect of being divorced or separated is greater for men compared to women whilst the effect of being widowed is greater for women. There is some indication that women who have never married exhibit better health outcomes whilst men who have never married exhibit worse outcomes although these effects are not significant. For men there is some indication that higher academic qualifications are associated with better mental health outcomes (contrast to baseline of no qualifications), although these effects, in general, are not significant. For women the effects are large and highly statistically significant with a clear gradient evident across educational categories. For men permanent income dominates the contemporaneous income effect with higher incomes being associated with better health outcomes. Whilst contemporaneous income is not significant, permanent income is except in the CMLE model. This suggests that conditioning on lagged health and initial period health removes the income effect on GHQ scores. Interestingly, for women both contemporaneous and permanent income are, in general, significantly related to GHQ score with greater incomes leading to better health. However, as with men, once initial and lagged health are included in the model the effect of permanent income becomes small and not significant. Further, the effect of contemporaneous income remains negative and significant. Few of the social class categories are significant for men. The three notable exceptions are skilled manual workers who, in general, report better mental health outcomes than the baseline of skilled non-manual and the unemployed and other social class groups which are associated with poor mental health outcomes. The coefficients on the latter two groups are large in comparison to the others. For women, again, the unemployed and other social class group are associated with poor mental health. However, whilst the coefficient on the unemployed is large and comparable to that found for men, the coefficient on other social class is smaller. Women engaged in family care also report significantly worse GHQ scores than the comparator group of skilled non-manual workers.

**Insert Table 6 here**

Allowing for individual heterogeneity is important in the variance components model; for men approximately 41% of unobserved variability is accounted for by individual heterogeneity, for women the figure is slightly less at 39%. Although these figures are significantly different to zero their magnitude suggest that persistence in mental health scores are modest and that time-varying random fluctuations dominate. Mobility in health status is slightly greater for men than women.

OLS, GMM IV, and CMLE provide estimates for the lagged dependent variable in a dynamic model. The OLS estimates are largest for both men and women due to the positive correlation between the lagged dependent variable and unobserved heterogeneity. For men the coefficient is .510 while for women the coefficient is .487. Although highly significant the absolute value of these coefficients do not suggest strong persistence (complete persistence would imply a coefficient of unity). Further, the coefficient for men is comparable in size to many of the other estimated coefficients and is smaller than the estimated effects for widowed, the unemployed and having a degree or higher degree.

The results of our attempts to decompose mobility estimates into components due to state dependence and heterogeneity are reported in columns 3 and 4 of Tables 5 and 6. Column 3 reports estimates based the first-differenced model estimated using GMM-IV. For men the estimate of state dependence is .147 and for women it is .116. These estimates are substantially lower than the OLS counterparts. As a comparator we also estimated model (5) using a within-groups estimator. Within-groups estimation of $\lambda$ is biased downwards [26] and results in an estimate for men of .056 and for women .057. The first-differenced GMM-IV estimates are substantially greater than those obtained from with-groups estimation suggesting that the instrument set employed are adequately correlated with the first-differenced lagged dependent variable. The instruments are also valid as evidenced by the Sargan test of over-identifying restrictions (men: $\chi^2_{44} = 42.56, p = .53$, women: $\chi^2_{44} = 65.23, p = .02$). The residuals in first-difference form exhibits first-order serial correlation for men and women but no second-order serial correlation for men ($z = 1.11, p = .27$). However there is evidence of second-order serial correlation for women ($z = 3.98, p = .0001$).

The CMLE allows us to partition observed mobility into components due to state dependence and individual heterogeneity due to the individual unobserved effect remaining in the model. The estimate of state dependence is .203 for men and .205 for women. These are greater than the GMM first-differenced estimates. The proportion of variance attributable to an unobserved individual effect is 25% for men and 20% from women. This represents a 40% reduction from the estimate obtained from the variance component MLE for men and a 49% reduction for women. Interestingly the coefficient estimates of initial period GHQ score are larger than their respective state dependence estimates (.283 for men, .306 for women). This suggests that initial health has a greater bearing on subsequent health outcomes than previous period's health. These results indicate substantial mobility across time around an underlying level of mental ill-health.

**Mobility across socio-economic groups**

Tables 7 and 8 present summary estimates of mobility for men and women respectively. The first column presents MLE of the proportion of variance attributable to the individual unobserved effect while the second column of results presents OLS estimates of the lagged health variable. These are followed by the first-differenced GMM-IV estimator of state dependence and finally CMLE of state dependence, initial period's health and the proportion of variance attributable to the unobserved individual effect.

**Insert Tables 7 & 8 here**

Our estimates of mobility derived from variance components MLE and OLS show clear gradients for both men and women. These are evident for ethnicity, educational attainment, income quintile, age and health status (healthy and unhealthy – see tables for definitions). Greater mobility is observed for ethnic groups other than white, for individuals with greater educational qualifications, for higher income groups, for younger individuals and for healthier individuals. Estimates derived from the lagged health variable estimated via OLS are larger than the mobility estimate derived from the proportion of variance attributable to an unobserved individual effect in the variance components model. In general, mobility estimates for women are smaller than those for men but these differences are often negligible. The differences in estimates within the different socio-economic groups are quite striking. For example, for men the increase in the estimated coefficient, $\hat{\rho}$, as one moves from degree or higher degree (DEGHDEG) to no qualifications (NOQUAL) is 50%. The corresponding increase for the OLS coefficient, $\hat{\lambda}$, is 33%. For women these differences are greater still at 78% and 56% respectively. Increases are even more pronounced across age quintiles. For men the difference in estimates as one moves from the 1st (youngest) to the 5th (oldest) age quintile is 51% for $\hat{\rho}$ and 68% for $\hat{\lambda}$. The increases for women are 106% and 78% respectively. The gradient across income quintiles is similar for men and women with an approximate 31% increase as one moves from the 1st to 5th quintile for $\hat{\rho}$ and a 20% increase for $\hat{\lambda}$. The change in mobility estimates across the healthy and unhealthy categories is far smaller for women than men. For both, there is greater mobility in the healthy category but for women the increase from healthy to unhealthy is 19% and 24% for $\hat{\rho}$ and $\hat{\lambda}$ respectively while the comparative increases for men are 63% and 47%.

Estimates of mobility vary across social class groups with some indication of a gradient. For both men and women the lowest estimates corresponding to greatest mobility are observed for professional, managerial and technical and skilled non-manual workers. The highest coefficients (least mobility) are observed for the retired, other social class group. The above resultsare displayed graphically for men in Figures 1 to 8.

**Insert Figures 1 to 8 here**

Results of separating the estimates of mobility into contributions due to state dependence and individual heterogeneity are shown in columns 3 and 4. Again estimates of state dependence from CMLE are larger than the corresponding estimates from first-differenced GMM-IV. It is notable that neither estimator produces a gradient in the state dependence estimates across the various categories of the socio-economic groups. This suggests that state dependence is not systematically related to socio-economic characteristics. However, we do observe gradients for $\hat{\rho}$ using CMLE. These are, in general, approximately 50% smaller than the corresponding estimates obtained using MLE but operate in the same direction. We also observe similar gradients across the parameter estimates of the initial period's GHQ score. These results suggest that differences in mobility across categories of socio-economic groups are not driven by state dependence but instead it appears to be largely dictated by differences in individual heterogeneity.

## Discussion and conclusions

Preventive health strategies and population health interventions should be targeted towards population groups most in need. Traditionally, these groups have been identified with analyses of cross-sectional data which provide a snap-shot of the distribution of health at a particular point in time. However, using cross-sectional analyses to identify risk groups might result in a low cost-effectiveness of population interventions. This is a particular problem for mental health policies, because mental illness comprise a variety of conditions which vary greatly in their intertemporal persistence. Analysis of individual longitudinal data can give information on systematic differences in persistence of health problems and help to develop more effective public health strategies.

In this paper we identify whether individuals within different social and economic strata experience differential mobility over time in their respective mental health distributions. Our measure of mental health is derived from a self-administered screening test aimed at detecting psychiatric disorders among respondents. We use data from eleven waves of the British Household Panel Survey (BHPS) and employ variance components random effects and dynamic models to measure the extent of mobility in our sample. The former partitions unobserved variability in health outcomes from an error components model into transitory and permanent components and uses the proportion of total variability attributed to the permanent component as a measure of mental health mobility. The smaller this proportion, the higher is health mobility. In the latter, the degree of mental health mobility is measured by the estimated coefficient on previous period's health status entered as an additional regressor. The smaller the coefficient, the higher is health mobility.

We find evidence of substantial mobility in mental health. This is apparent for both males and females. Also, we find evidence of systematic differences in mobility across socio-economic groups. These are evident for ethnicity, educational attainment, income quintile, age and health status. In general individuals from an ethnic origin other than white experience worse mental health outcomes (although these effects are not significant) but greater mobility over time compared to white ethnic groups. Individuals from lower income groups are associated with greater mental ill-health but are also associated with greater permanence over time compared to individuals from higher income groups. Further, for men long-term income effects dominate short-run contemporaneous effects. For women both short-term and long-term income effects appear important determinants of mental health. Greater academic qualifications are in general associated with better mental health outcomes except for men when the model is conditioned on state dependence and initial period's health. Greater qualifications are also associated with higher mobility over time. Cross-sectional analyses find that mental health problems are concentrated among groups with low educational status (e.g. Henderson [5]., Goldberg [6]). Our results imply that mental health problems among these risk groups are aggravated by the fact that they tend to be of a more permanent nature. Mental health deteriorates with age and becomes more permanent in nature. The unemployed, and individuals categorised as other social class report worse GHQ scores. This finding for the unemployed have been reported elsewhere [5,6,27]. Women occupied with family care also report worse GHQ scores. However, the retired and other social class group experience greatest permanence in outcomes over time.

Decomposing our estimates of health mobility into components due to state dependence and unobserved individual heterogeneity suggests that it is the latter that drives the observed gradients in mobility across the categories of the various socio-economic groups considered. Including state dependence improves the fit of the models and reduces the impact of individual unobserved heterogeneity. While the estimated coefficients are positive and significant the absolute value of the state dependence parameters are small. Conditioning on state dependence and initial period's health status reduces the contribution of unobserved permanent heterogeneity from approximately 40% of total unexplained variation to approximately 22%.

The associations between socio-economic status, mental health and observed mobility in health outcomes have implications for the efficient and equitable allocation of resources. Consideration of both the level of ill-health and the extent of mobility over time are important if mental health policies are to be judged either on the grounds of cost-effectiveness or whether they are targeted at those most in need.

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*Table 1: Variable definitions*

| | |
|---|---|
| GHQ | Self-Assessed psychological health (higher score = poorer health) |
| MARCOUP | 1 if married or living as a couple, 0 otherwise |
| WIDOWED | 1 if widowed, 0 otherwise |
| DIVSEP | 1 if divorced or separated, 0 otherwise |
| NVRMAR | 1 if never married, 0 otherwise |
| DEGHDEG | 1 if highest academic qualification is a degree or higher degree, 0 otherwise |
| HNDALEV | 1 if highest academic qualification is HND or A Level, 0 otherwise |
| OCSE | 1 if highest academic qualification is O level or CSE, 0 otherwise |
| NOQUAL | 1 if no qualifications, 0 otherwise |
| HHSIZE | Number of people in household including respondent |
| NCHO4 | Number of children in household aged 0-4 |
| NCH511 | Number of children in household aged 5-11 |
| NCH1218 | Number of children in household aged 12-18 |
| LNINC | Natural log of equivalised annual real household income in pounds |
| AGE | Age in years at 1st December of current wave |
| WHITE | 1 if member of white ethnic group, o otherwise |
| OTHETH | 1 if member of non-white ethnic group, 0 otherwise |
| PROF | 1 if Registrar General's social class of professional, 0 otherwise |
| MANAGE | 1 if Registrar General's social class of managerial, 0 otherwise |
| SKNONM | 1 if Registrar General's social class of skilled non-manual, 0 otherwise |
| SLMANAR | 1 if Registrar General's social class of skilled manual, 0 otherwise |
| UNPSKL | 1 if Registrar General's social class of unskilled, partly skilled, 0 otherwise |
| UNEMP | 1 if unemployed, 0 otherwise |
| RETIRED | 1 if retired, 0 otherwise |
| FAMCARE | 1 if family care, 0 otherwise |
| SCOTHER | 1 if Registrar General's social class is other, 0 otherwise |

*Table 2: Variable means by sub-samples of "healthy" and "unhealthy"*

| | FULL SAMPLE | | MEN | | WOMEN | |
|---|---|---|---|---|---|---|
| | "Healthy" | "Unhealthy" | "Healthy" | "Unhealthy" | "Healthy" | "Unhealthy" |
| | NT = 20735 | NT = 15262 | NT = 11749 | NT = 8464 | NT = 8261 | NT = 10730 |
| GHQ | 7.66 | 16.50 | 7.40 | 15.04 | 7.83 | 16.57 |
| MARCOUP | .697 | .652 | .715 | .718 | .676 | .620 |
| WIDOWED | .068 | .101 | .037 | .045 | .105 | .135 |
| DIVSEP | .060 | .122 | .048 | .076 | .076 | .136 |
| NVRMAR | .174 | .125 | .200 | .160 | .142 | .110 |
| DEGHDEG | .143 | .117 | .139 | .123 | .140 | .105 |
| HNDALEV | .260 | .209 | .288 | .274 | .219 | .174 |
| OCSE | .292 | .267 | .292 | .240 | .312 | .282 |
| NOQUAL | .306 | .406 | .281 | .363 | .328 | .439 |
| HHSIZE | 2.74 | 2.73 | 2.80 | 2.79 | 2.66 | 2.72 |
| NCHO4 | .137 | .143 | .139 | .138 | .136 | .147 |
| NCH511 | .225 | .296 | .223 | .264 | .227 | .313 |
| NCH1218 | .155 | .198 | .157 | .182 | .148 | .212 |
| LNINC | 9.677 | 9.498 | 9.708 | 9.563 | 9.648 | 9.462 |
| AGE | 46.50 | 47.03 | 45.96 | 46.98 | 47.16 | 47.44 |
| WHITE | .974 | .960 | .978 | .959 | .975 | .964 |
| OTHETH | .026 | .040 | .022 | .041 | .025 | .036 |
| PROF | .041 | .030 | .056 | .057 | .021 | .017 |
| MANTECH | .206 | .176 | .213 | .212 | .191 | .165 |
| SKNONM | .137 | .146 | .091 | .077 | .200 | .175 |
| SKMANAR | .151 | .084 | .238 | .177 | .046 | .043 |
| UNPSKL | .115 | .104 | .115 | .091 | .117 | .109 |
| UNEMP | .037 | .044 | .048 | .065 | .020 | .030 |
| RETIRED | .214 | .186 | .201 | .183 | .224 | .194 |
| FAMCARE | .066 | .130 | .009 | .010 | .144 | .190 |
| SCOTHER | .033 | .100 | .030 | .128 | .037 | .075 |

1. The categories "Healthy" and "Unhealthy" were derived as follows: The distribution of GHQ scores were first categorised into quintiles. "Healthy" individuals are those for whom the mode of the quintile categories across the waves was 1, "Unhealthy" individuals are those for whom the mode of the quintile categories across the waves was 5.

*Table 3: Correlation Matrices*

a) *Men*

| Wave | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 11 |
|---|---|---|---|---|---|---|---|---|---|---|---|
| 1 | 1.00 | | | | | | | | | | |
| 2 | .489 | 1.00 | | | | | | | | | |
| 3 | .422 | .531 | 1.00 | | | | | | | | |
| 4 | .388 | .451 | .524 | 1.00 | | | | | | | |
| 5 | .383 | .454 | .484 | .526 | 1.00 | | | | | | |
| 6 | .338 | .393 | .414 | .471 | .556 | 1.00 | | | | | |
| 7 | .316 | .348 | .383 | .455 | .451 | .532 | 1.00 | | | | |
| 8 | .328 | .374 | .385 | .421 | .436 | .467 | .525 | 1.00 | | | |
| 9 | .315 | .361 | .373 | .406 | .392 | .442 | .465 | .536 | 1.00 | | |
| 10 | .353 | .359 | .391 | .404 | .388 | .409 | .433 | .455 | .544 | 1.00 | |
| 11 | .355 | .351 | .363 | .401 | .386 | .392 | .395 | .441 | .477 | .538 | 1.00 |

b) *Women*

| Wave | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 11 |
|---|---|---|---|---|---|---|---|---|---|---|---|
| 1 | 1.00 | | | | | | | | | | |
| 2 | .484 | 1.00 | | | | | | | | | |
| 3 | .444 | .506 | 1.00 | | | | | | | | |
| 4 | .395 | .438 | .516 | 1.00 | | | | | | | |
| 5 | .363 | .386 | .408 | .502 | 1.00 | | | | | | |
| 6 | .357 | .370 | .387 | .435 | .470 | 1.00 | | | | | |
| 7 | .332 | .311 | .322 | .368 | .435 | .456 | 1.00 | | | | |
| 8 | .322 | .302 | .348 | .393 | .402 | .444 | .525 | 1.00 | | | |
| 9 | .327 | .328 | .352 | .352 | .391 | .411 | .448 | .504 | 1.00 | | |
| 10 | .331 | .309 | .354 | .331 | .334 | .370 | .387 | .463 | .521 | 1.00 | |
| 11 | .324 | .325 | .315 | .323 | .329 | .347 | .355 | .422 | .464 | .518 | 1.00 |

*Table 4: Transition Matrices*

*a) Men*

| GHQ Quintile | 1 | 2 | 3 | 4 | 5 | N |
|---|---|---|---|---|---|---|
| 1 | .571 | .125 | .191 | .052 | .061 | 9253 |
| 2 | .354 | .157 | .327 | .075 | .087 | 3203 |
| 3 | .203 | .117 | .393 | .149 | .139 | 8523 |
| 4 | .113 | .064 | .315 | .249 | .260 | 3773 |
| 5 | .094 | .041 | .183 | .161 | .522 | 5928 |
| N | 9127 | 3133 | 8438 | 3883 | 6099 | 30680 |

b) *Women*

| GHQ Quintile | 1 | 2 | 3 | 4 | 5 | N |
|---|---|---|---|---|---|---|
| 1 | .492 | .284 | .101 | .061 | .063 | 7680 |
| 2 | .214 | .385 | .197 | .109 | .095 | 9806 |
| 3 | .098 | .248 | .336 | .174 | .145 | 7393 |
| 4 | .086 | .171 | .248 | .227 | .267 | 5402 |
| 5 | .069 | .119 | .135 | .187 | .491 | 7200 |
| N | 7559 | 9561 | 7500 | 5397 | 7464 | 37481 |

*Table 5: MEN*

| GHQ | MEN | | | |
|---|---|---|---|---|
| | MLE | OLS | GMM IV 1st Diff | CMLE |
| | (1) | (2) | (3) | (4) |
| | N = 4549 | | N = 3640 | N = 4012 |
| | NT = 35279 | NT = 29708 | NT = 25198 | NT = 29708 |
| GHQ(t-1) | | .510 (.005) | .147 (.014) | .203 (.007) |
| AGE | .526 (.050) | .335 (.039) | - | .396 (.052) |
| AGE2 | -1.059 (.102) | -.680 (.079) | -.526 (.355) | -.816 (.105) |
| AGE3 | .662 (.065) | .420 (.049) | .313 (.223) | .514 (.066) |
| WIDOWED | .922 (.251) | .654 (.314) | 3.427 (.609) | .799 (.281) |
| NVRMAR | .333 (.136) | -.065 (.169) | .430 (.288) | .100 (.153) |
| DIVSEP | 1.339 (.171) | .552 (.214) | 1.776 (.411) | .969 (.191) |
| HHSIZE | .100 (.040) | .153 (.051) | .171 (.080) | .149 (.045) |
| NCHO4 | -.112 (.078) | -.144 (.098) | -.236 (.146) | -.119 (.087) |
| NCH511 | -.084 (.063) | -.115 (.097) | -.178 (.143) | -.095 (.073) |
| NCH1218 | .048 (.066) | -.009 (.087) | -.175 (.133) | .014 (.078) |
| PROF | .074 (.170) | -.024 (.209) | .063 (.247) | .086 (.187) |
| MANTECH | -.097 (.119) | .067 (.146) | .129 (.194) | .077 (.131) |
| SKMANAR | -.361 (.130) | -.353 (.162) | -.302 (.207) | -.396 (.145) |
| UNPSKL | -.117 (.139) | -.369 (.172) | -.262 (.217) | -.292 (.154) |
| UNEMP | 1.731 (.156) | 1.154 (.197) | 1.797 (.310) | 1.434 (.176) |
| RETIRED | -.142 (.163) | -.356 (.201) | -.406 (.284) | -.259 (.181) |
| FAMCARE | .897 (.281) | .529 (.452) | .839 (.539) | .339 (.416) |
| SCOTHER | 1.581 (.166) | .663 (.204) | 1.043 (.312) | 1.150 (.183) |
| LNINC | -.010 (.051) | .071 (.064) | .048 (.088) | .023 (.058) |
| MLNINC | -.471 (.138) | -.279 (.092) | - | -.186 (.122) |
| DEGHDEG | -.271 (.24) | -.143 (.099) | - | -.088 (.168) |
| HNDALEV | -.236 (.158) | -.133 (.074) | - | -.111 (.125) |
| OCSE | -.172 (.150) | -.160 (.071) | - | -.188 (.119) |
| OTHETH | .454 (.279) | .204 (.143) | - | .232 (.234) |
| CONS | 6.688 (1.50) | 2.525 (.867) | .202 (.192) | 1.521 (1.328) |
| GHQ(0) | | | | .283 (.010) |
| $\sigma_\eta$ | 3.101 (.041) | | | 2.100 (.042) |
| $\sigma_\varepsilon$ | 3.690 (.015) | | | 3.685 (.017) |
| $\rho$ | .414 (.007) | | | .245 (.008) |
| Log Likelihood | -100066 | | | -83230 |

Note:

1. Time dummies and means of time-varying regressors have been suppressed from results.
2. Standard errors in parentheses.
3. RESET tests – MLE: $\chi^2_3 = 24.2$, p < .000. OLS: F(3, 29655) = 44.05, p < .000; CMLE: $\chi^2_3 = 7.5$, p = .058.
4. Within-groups of model (5) gives $\hat{\lambda} = .056$, SE = (.006).
5. Hausman test of random versus fixed effects: $\chi^2_{30} = 43.2$, $p = .06$.
6. Sargan test of over-identifying restrictions: $\chi^2_{44}$ = 42.56; P = 0.5332. Arellano-Bond test that average autocovariance in residuals of order 1 is 0: H0: no autocorrelation z = -28.2; P = 0.0000. Arellano-Bond test that average autocovariance in residuals of order 2 is 0: H0: no autocorrelation z = 1.11; Pr > z = 0.2681.

*Table 6: WOMEN*

| GHQ | WOMEN | | | |
|---|---|---|---|---|
| | MLE | OLS | GMM IV 1st Diff | CMLE |
| | (1) | (2) | (3) | (4) |
| | N = 5254 | | N = 4351 | N = 4722 |
| | NT = 42778 | NT = 36358 | NT = 30952 | NT = 36358 |
| GHQ(t-1) | | .487 (.005) | .116 (.013) | .205 (.006) |
| AGE | .357 (.052) | .242 (.042) | - | .255 (.054) |
| AGE2 | -.714 (.105) | -.484 (.083) | -.738 (.282) | -.519 (.107) |
| AGE3 | .437 (.065) | .295 (.051) | .486 (.175) | .327 (.066) |
| WIDOWED | 1.708 (.186) | .886 (.233) | 2.815 (.376) | 1.367 (.212) |
| NVRMAR | -.204 (.160) | -.349 (.198) | -.319 (.376) | -.368 (.182) |
| DIVSEP | .899 (.149) | .335 (.185) | 1.587 (.354) | .617 (.168) |
| HHSIZE | .096 (.044) | .094 (.055) | .097 (.088) | .102 (.050) |
| NCHO4 | .180 (.084) | .062 (.105) | .110 (.155) | .115 (.095) |
| NCH511 | -.309 (.066) | -.151 (.084) | -.198 (.149) | -.217 (.076) |
| NCH1218 | -.075 (.068) | -.003 (.088) | -.133 (.152) | -.039 (.080) |
| PROF | .194 (.274) | .052 (.332) | -.520 (.417) | .124 (.300) |
| MANTECH | .153 (.111) | .151 (.136) | .046 (.198) | .165 (.123) |
| SKMANAR | -.166 (.154) | -.292 (.189) | -.522 (.249) | -.218 (.171) |
| UNPSKL | -.044 (.120) | -.207 (.148) | -.333 (.209) | -.120 (.134) |
| UNEMP | 1.631 (.181) | 1.378 (.226) | 1.640 (.358) | 1.603 (.205) |
| RETIRED | .118 (.136) | .011 (.167) | .232 (.219) | .034 (.151) |
| FAMCARE | .595 (.113) | .340 (.141) | .613 (.205) | .498 (.127) |
| SCOTHER | .955 (.162) | .446 (.198) | .374 (.299) | .746 (.179) |
| LNINC | -.202 (.053) | -.137 (.065) | -.184 (.089) | -.176 (.059) |
| MLNINC | -.404 (.136) | -.193 (.092) | - | -.092 (.116) |
| DEGHDEG | -1.075 (.236) | -.565 (.110) | - | -.567 (.177) |
| HNDALEV | -.568 (.175) | -.355 (.083) | - | -.338 (.133) |
| OCSE | -.607 (.146) | -.345 (.070) | - | -.289 (.111) |
| OTHETH | .139 (.294) | .051 (.152) | - | .028 (.234) |
| CONS | 12.144 (1.479) | 5.946 (.880) | .464 (.167) | 4.897 (1.278) |
| GHQ(0) | | | | .306 (.009) |
| $\sigma_\eta$ | 3.327 (.041) | | | 2.135 (.041) |
| $\sigma_\varepsilon$ | 4.208 (.015) | | | 4.258 (.017) |
| $\rho$ | .385 (.006) | | | .201 (.007) |
| Log Likelihood | -126617 | | | -106699 |

Note:

1. Time dummies and means of time-varying regressors have been suppressed from results.
2. Standard errors in parentheses.
3. RESET tests – MLE: $\chi^2_3 = 6.28$, p < .099. OLS: F(3, 36305) = 34.01, p < .000; CMLE: $\chi^2_3 = 1.88$, p = .598.
4. Within-groups of model (5) gives $\hat{\lambda} = .057$, SE = (.006).
5. Hausman test of random versus fixed effects for MLE variance components model: $\chi^2_{30} = 21.7$, $p = .87$.
6. Sargan test of over-identifying restrictions: $\chi^2_{44}$ = 65.23; P = 0.02. Arellano-Bond test that average autocovariance in residuals of order 1 is: H0: no autocorrelation z = -32.58; P = 0.0000. Arellano-Bond test that average autocovariance in residuals of order 2 is: H0: no autocorrelation z = 3.98; Pr > z = 0.0001.

*Table 7: Sub-sample results - MEN*

| | MLE | OLS | GMM IV 1st Diff | | CMLE | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | | (4) | |
| | $\hat{\rho}$ | $\hat{\lambda}$ | $\hat{\lambda}$ | $\hat{\lambda}$ | $\hat{\alpha}_2$ | $\hat{\rho}$ |
| ALL DATA | .414 (.007) | .510 (.005) | .147 (.014) | .203 (.007) | .283 (.010) | .245 (.008) |
| ETHNICITY | | | | | | |
| WHITE | .417 (.007) | .511 (.005) | .147 (.015) | .200 (.007) | .286 (.010) | .247 (.008) |
| OTHETH | .300 (.035) | .422 (.030) | .120 (3.96) | .242 (.039) | .149 (.058) | .164 (.039) |
| EDUCATION | | | | | | |
| DEGHDEG | .318 (.018) | .420 (.015) | .185 (.033) | .195 (.019) | .250 (.027) | .177 (.019) |
| HNDALEV | .379 (.013) | .483 (.010) | .150 (.025) | .207 (.013) | .257 (.018) | .214 (.014) |
| OCSE | .409 (.013) | .498 (.010) | .101 (.028) | .179 (.013) | .277 (.019) | .265 (.016) |
| NOQUAL | .469 (.012) | .557 (.009) | .153 (.028) | .214 (.012) | .313 (.017) | .277 (.028) |
| INCOME | | | | | | |
| 1st QUINTILE | .477 (.015) | .567 (.011) | .128 (.034) | .208 (.016) | .318 (.022) | .294 (.019) |
| 2nd QUINTILE | .435 (.015) | .539 (.011) | .163 (.038) | .218 (.015) | .262 (.021) | .267 (.018) |
| 3rd QUINTILE | .386 (.016) | .453 (.012) | .133 (.028) | .160 (.015) | .261 (.021) | .246 (.017) |
| 4th QUINTILE | .367 (.015) | .472 (.012) | .152 (.029) | .200 (.016) | .292 (.022) | .200 (.017) |
| 5th QUINTILE | .329 (.015) | .451 (.012) | .145 (0.30) | .210 (.016) | .265 (.023) | .183 (.016) |
| AGE | | | | | | |
| 1st QUINTILE | .285 (.014) | .385 (.012) | .124 (.026) | .171 (.015) | .203 (.021) | .178 (.016) |
| 2nd QUINTILE | .354 (.015) | .456 (.012) | .148 (.030) | .207 (.016) | .233 (.021) | .195 (.017) |
| 3rd QUINTILE | .399 (.015) | .494 (.012) | .159 (.027) | .182 (.015) | .273 (.023) | .267 (.018) |
| 4th QUINTILE | .432 (.016) | .537 (.011) | .170 (.037) | .234 (.016) | .283 (.020) | .227 (.017) |
| 5th QUINTILE | .586 (.014) | .649 (.010) | .114 (.042) | .221 (.016) | .401 (.022) | .331 (.019) |
| SOCIAL CLASS | | | | | | |
| PROF | .315 (.027) | .415 (.022) | .136 (.037) | .162 (.028) | .296 (.040) | .175 (.028) |
| MANTECH | .323 (.014) | .431 (.011) | .149 (.028) | .196 (.014) | .200 (.019) | .204 (.015) |
| SKNONM | .303 (.023) | .449 (.020) | .182 (.045) | .232 (.026) | .221 (.037) | .166 (.025) |
| SKMANAR | .376 (.014) | .464 (.011) | .136 (.027) | .187 (.015) | .267 (.019) | .215 (.016) |
| UNPSKL | .369 (.020) | .497 (.016) | .186 (.046) | .217 (.022) | .239 (.028) | .212 (.024) |
| UNEMP | .396 (.038) | .457 (.031) | .060 (.054)$ | .166 (.041) | .349 (.062) | .217 (.047) |
| FAMCARE | - | - | | - | - | - |
| RETIRED | .585 (.014) | .651 (.010) | .081 (.041) | .211 (.016) | .416 (.022) | .336 (.019) |
| SCOTHER | .482 (.029) | .605 (.020) | .154 (.068) | .305 (.030) | .265 (.037) | .232 (.034) |
| HEALTH | | | | | | |
| HEALTHY | .128 (.006) | .236 (.007) | .123 (.014) | .143 (.009) | .049 (.010) | .090 (.007) |
| UNHEALTHY | .208 (.009) | .348 (.009) | .179 (.019) | .220 (.011) | .099 (.012) | .112 (.009) |

Notes:
1. All GMM 1st difference models passed tests for over-identifying restrictions at the 5% level.
2. All GMM 1st difference models passed tests for autocorrelation of order 2 (at 5% level) except $: z = 2.91, p = .004.
3. Individuals are classified as being healthy if their mean GHQ score was lower than the sample mean GHQ score. Individuals are classified as being unhealthy if their mean GHQ score was higher than the sample mean GHQ score.
4. Too few observations for FAMCARE to provide reliable estimates.

*Table 8: Sub-sample results - WOMEN*

| | MLE | OLS | GMM IV 1st Diff | | CMLE | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | | (4) | |
| | $\hat{\rho}$ | $\hat{\lambda}$ | $\hat{\lambda}$ | $\hat{\lambda}$ | $\hat{\alpha}_2$ | $\hat{\rho}$ |
| ALL DATA | .385 (.006) | .487 (.005) | .116 (.013) | .205 (.006) | .306 (.009) | .201 (.007) |
| ETHNICITY | | | | | | |
| WHITE | .385 (.006) | .488 (.005) | .116 (.013) \$1 | .205 (.006) | .305 (.009) | .201 (.007) |
| OTHETH | .338 (.035) | .431 (.029) | .064 (.077) | .178 (.037) | .336 (.050) | .174 (.037) |
| EDUCATION | | | | | | |
| DEGHDEG | .262 (.018) | .362 (.016) | .060 (.031) | .165 (.019) | .215 (.028) | .153 (.018) |
| HNDALEV | .314 (.014) | .425 (.011) | .111 (.029) | .203 (.015) | .228 (.021) | .176 (.015) |
| OCSE | .341 (.011) | .447 (.009) | .123 (.022) | .191 (.011) | .295 (.016) | .181 (.011) |
| NOQUAL | .466 (.010) | .564 (.007) | .128 (.028) | .223 (.010) | .347 (.013) | .237 (.011) |
| INCOME | | | | | | |
| 1st QUINTILE | .436 (.014) | .519 (.011) | .091 (.032) | .191 (.015) | .353 (.020) | .226 (.016) |
| 2nd QUINTILE | .400 (.014) | .508 (.010) | .141 (.029) | .236 (.014) | .314 (.019) | .178 (.014) |
| 3rd QUINTILE | .397 (.014) | .494 (.010) | .095 (.027) | .183 (.014) | .319 (.020) | .225 (.015) |
| 4th QUINTILE | .327 (.013) | .439 (.011) | .131 (.029) | .203 (.014) | .274 (.019) | .167 (.014) |
| 5th QUINTILE | .295 (.013) | .417 (.011) | .097 (.022) \$2 | .202 (.014) | .226 (.021) | .171 (.014) |
| AGE | | | | | | |
| 1st QUINTILE | .266 (.012) | .353 (.011) | .034 (.025) | .150 (.014) | .228 (.019) | .159 (.013) |
| 2nd QUINTILE | .316 (.014) | .425 (.011) | .127 (.025) | .194 (.014) | .262 (.021) | .169 (.014) |
| 3rd QUINTILE | .349 (.014) | .469 (.011) | .181 (.027) | .224 (.014) | .251 (.019) | .179 (.014) |
| 4th QUINTILE | .463 (.014) | .567 (.010) | .111 (.033) | .237 (.014) | .350 (.019) | .228 (.015) |
| 5th QUINTILE | .550 (.013) | .629 (.010) | .119 (.037) | .229 (.015) | .423 (.020) | .266 (.017) |
| SOCIAL CLASS | | | | | | |
| PROF | .212 (.045) | .267 (.046) | -.035 (.106) | .084 (.053) | .343 (.080) | .109 (.042) |
| MANTECH | .318 (.014) | .447 (.011) | .110 (.026) | .219 (.015) | .244 (.021) | .174 (.015) |
| SKNONM | .287 (.013) | .373 (.011) | .067 (.024) \$3 | .142 (.013) | .271 (.019) | .162 (.013) |
| SKMANAR | .375 (.030) | .450 (.023) | .165 (.059) | .189 (.031) | .346 (.041) | .150 (.029) |
| UNPSKL | .374 (.019) | .482 (.014) | .118 (.043) | .215 (.019) | .252 (.028) | .215 (.020) |
| UNEMP | .177 (.056) | .160 (.065) | -123 (.068) | .045 (.063) | .309 (.065) | - |
| FAMCARE | .398 (.105) | -.497 (.012) | .131 (.034) | .213 (.016) | .334 (.022) | .189 (.016) |
| RETIRED | .522 (.012) | .629 (.009) | .162 (.030) | .264 (.013) | .375 (.018) | .250 (.015) |
| SCOTHER | .425 (.037) | .535 (.026) | .104 (.066) | .283 (.038) | .230 (.046) | .182 (.040) |
| HEALTH | | | | | | |
| HEALTHY | .134 (.006) | .245 (.007) | .110 (.013) | .152 (.008) | .089 (.009) | .078 (.006) |
| UNHEALTHY | .160 (.007) | .305 (.008) | .143 (.017)* \$5 | .219 (.010) | .096 (.011) | .068 (.007) |

Note: 1 All GMM 1st difference models passed tests for over-identifying restrictions at the 1% level except *: $\chi^2_{44} = 81.35$, $p = .0005$.

2. All GMM 1st difference models passed tests for autocorrelation of order 2 except:
\$1: z = 3.78, p = .0002; \$2: z = 2.62, p = 0.009; \$3: z = 3.17, p = 0.002; \$4: z= 4.28, p = 0.0004.

3. Individuals are classified as being healthy if their mean GHQ score was lower than the sample mean GHQ score. Individuals are classified as being unhealthy if their mean GHQ score was higher than the sample mean GHQ score.

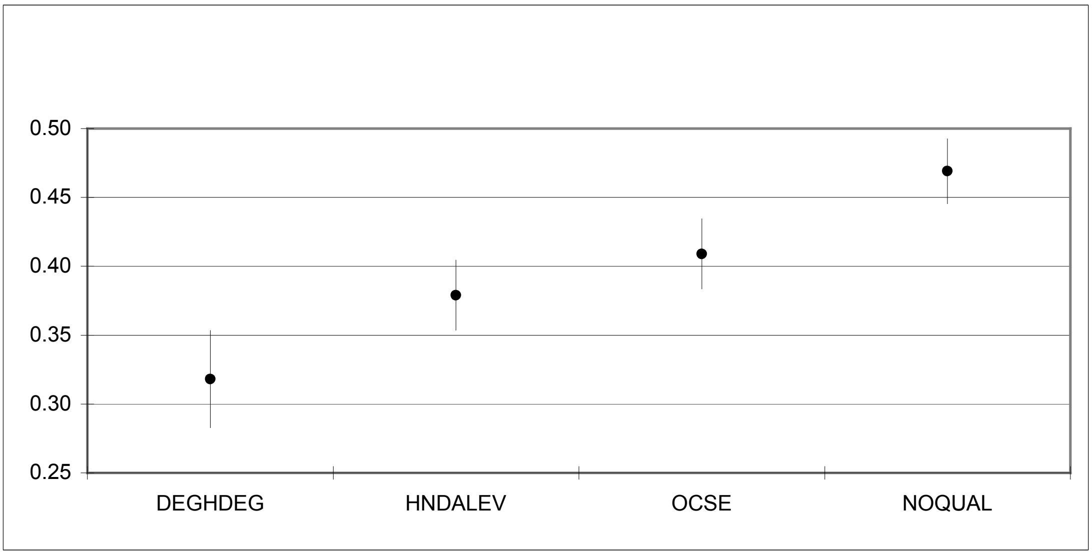


Figure 1: MLE estimates of $\rho$ by education group for men.

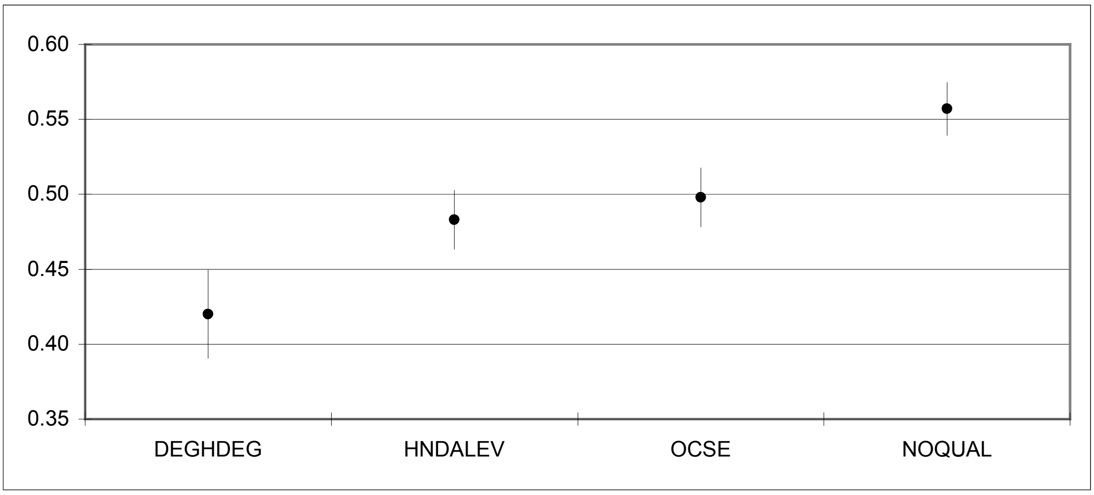


Figure 2: OLS estimates of $\lambda$ by education group for men.

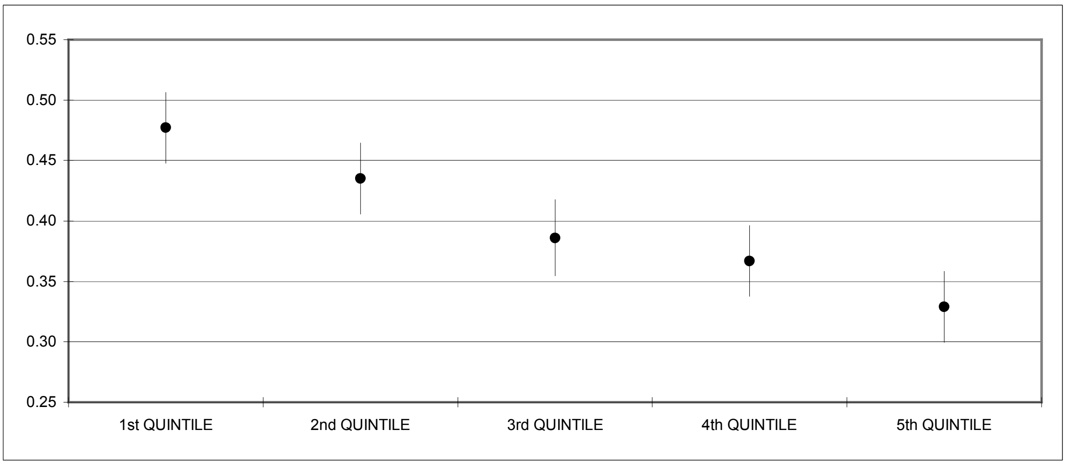


Figure 3: MLE estimates of $\rho$ by income quintile for men.

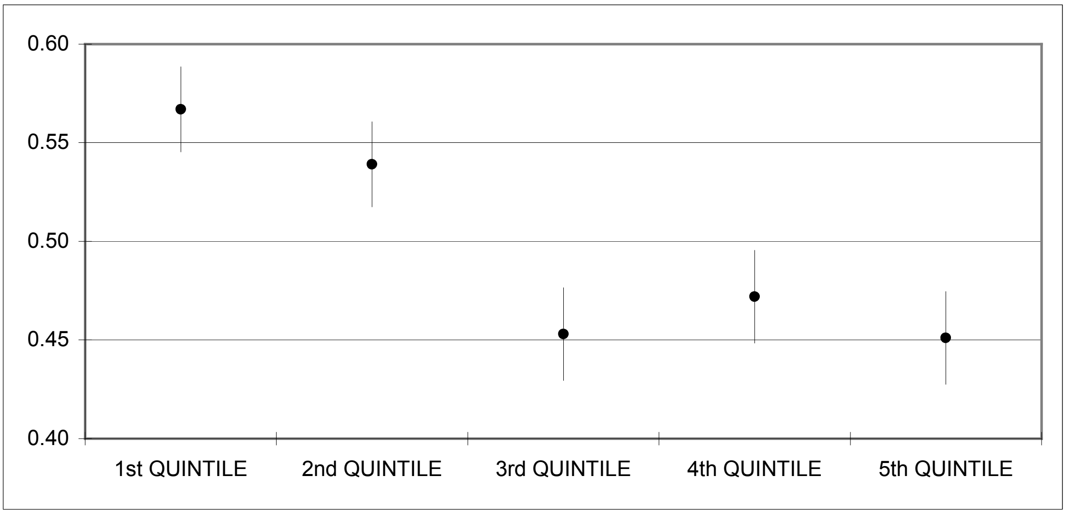


Figure 4: OLS estimates of $\lambda$ by income quintile for men.

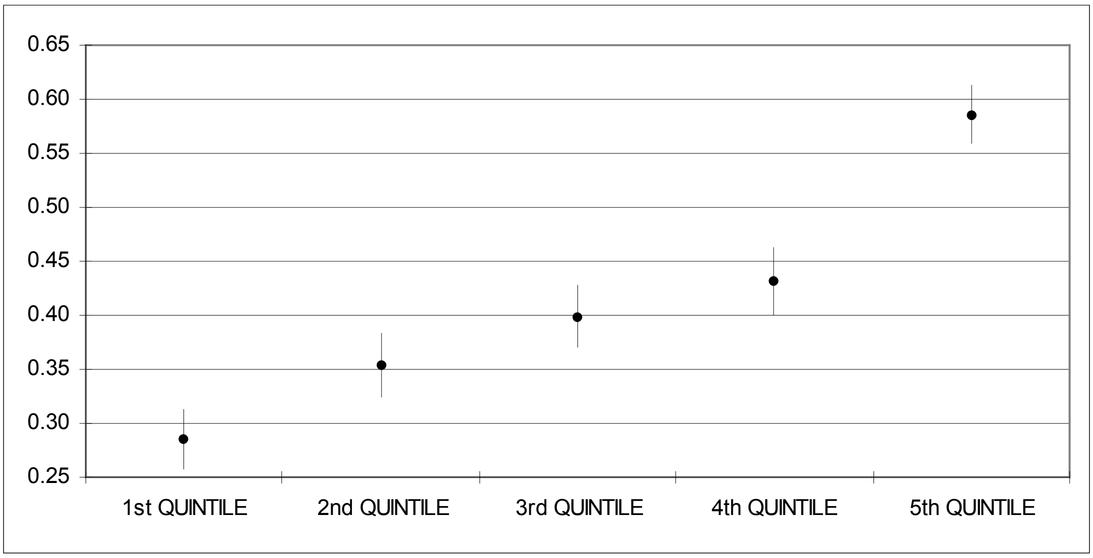


Figure 5: MLE estimates of $\rho$ by age quintile for men.

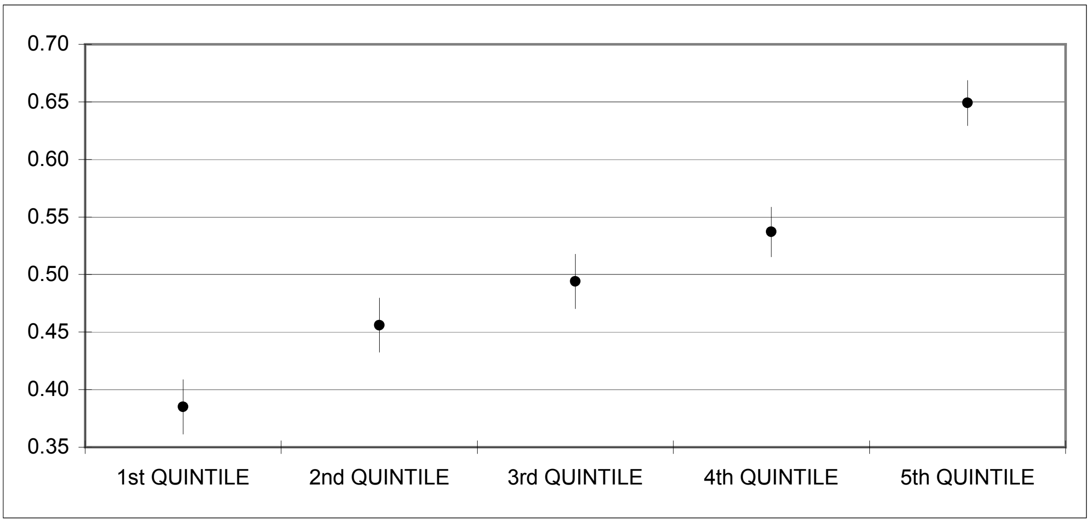


Figure 6: OLS estimates of $\lambda$ by age quintile for men.

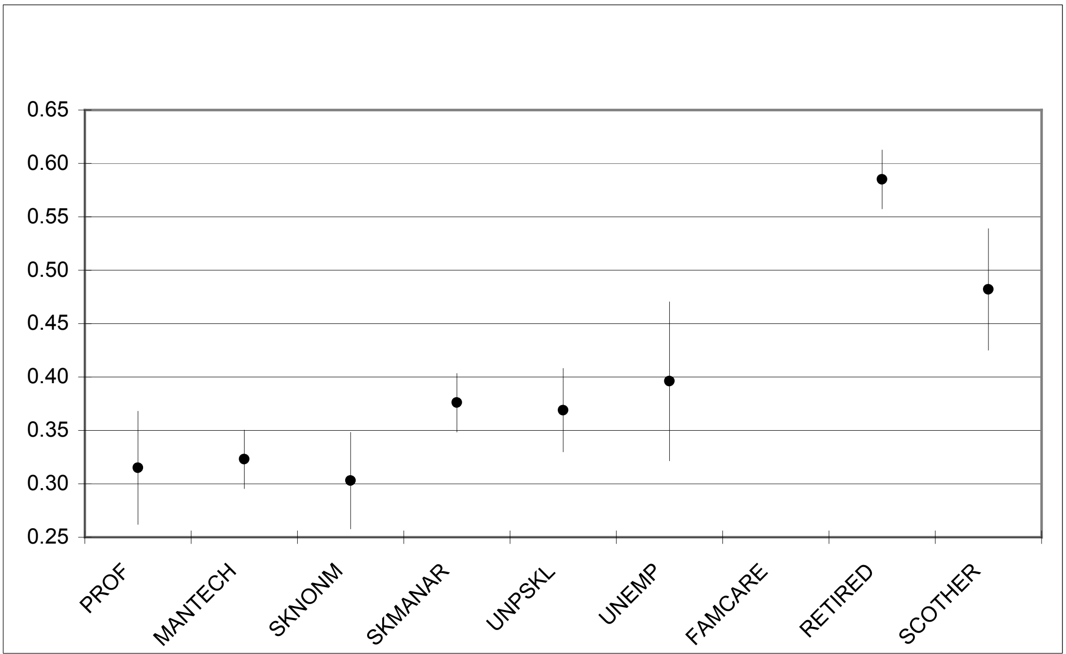


Figure 7: MLE estimates of $\rho$ by social class group for men.

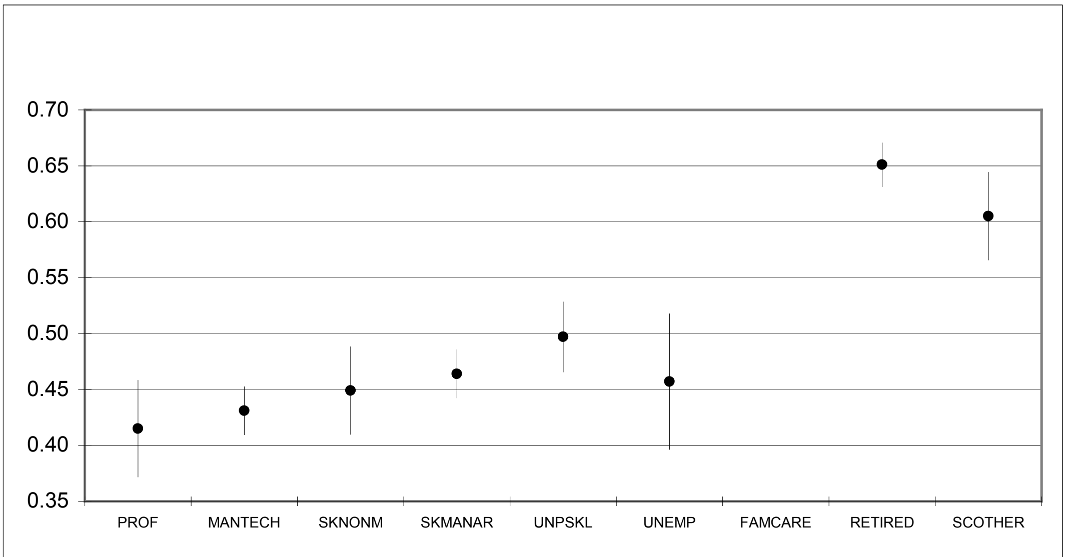


Figure 8: OLS estimates of $\lambda$ by social class group for men.