The Journal of Mental Health Policy and Economics
J Ment Health Policy Econ **7**, 99-106 (2004)

Determinants of Self-reported Mental Health Using the British Household Panel Survey

Antonio Rodríguez Andrés[1]*

[1]*Department of Economics, University of Southern Denmark, Odense, Denmark*

Abstract

Background: The study of self-reported mental health is a fairly recent area for economists, although sociologists, psychologists and public health specialists have been studying it for years. One methodological problem with earlier research is that there are many unobserved characteristics of individuals that may be correlated with self-reported mental health. Neglecting these factors may lead to biased estimates of the effects of variables such as income, education, health, etc. Panel data enables us to control for unobserved individual specific effects, whereas a cross-section study or time series study cannot.
Aims of the Study: This paper examines the determinants of self-reported mental health in UK using data from the first eight waves of the British Household Panel Survey. In particular, we are interested in assessing the effect of education on self-reported mental health which other studies have ignored.
Methods: The measure of self-reported mental health used in this paper is the General Health Questionnaire (GHQ). To account for the possible correlation between the unobserved individual effects and some explanatory variables, a Hausman Taylor's instrumental variables estimator (HT) is employed. In order to derive this estimator, one has to distinguish between variables that are correlated with the individual specific effects (*endogenous*) and variables which are uncorrelated with the individual specific effects (*exogenous*). This HT estimator also allows for estimating the parameters corresponding with time invariant variables such as education and ethnicity.
Results: The evidence presented here confirms that mental health scores mentioned on the GHQ are significantly related to job status, age, marital status and self-assessed health status. The results also show no evidence that income impacts on self-reported mental health. Ethnicity is also found to deteriorate self-reported mental health yet the effect is not significant. The results of this paper also show that education had no significant impact on self-reported mental health.
Implications for Mental Health Policy: Issues related to unemployment and social cohesion may be relevant factors in the prevention of mental illness. Policies aimed at improving these factors have an impact on the mental health status of society. In consideration of the evidence of gender differential in mental health, mental health policies should take into account properly this issue.
Implications for Further Research: In order to draw definite conclusions, it is important to formally test the presence of attrition bias as well as expand the sample to include more waves. Still, we are concerned about the issue of weak correlation between the instruments and potential endogenous variables. Additionally, we have to bear in mind that inconsistent estimates may potentially occur if the partition of the variables in subsets of endogenous and exogenous is not correctly specified. These issues need further research. The estimation technique also presented in this paper may be applied to a wide range of health services research.

Received 9 October 2003; accepted 3 June 2004

Introduction

Mental health problems range from depression, anxiety, schizophrenia as well as suicidal tendencies and even to worries we experience during our day to day life. Poor mental health is not only an individual tragedy but also a serious loss of productive assets for the society. According to the Mental Health Foundation,[1] in the United Kingdom, one in four individuals will experience some sort of mental health problems during the year. It is also reported women, in general, have poorer mental health than men. Similarly, those who identify as minorities in the UK have poorer mental health. Therefore, it seems to be important to thoroughly investigate the determinants of mental health in Britain as well as its gender differences.

The determinants of self-reported mental health have been an area of active research and debate in recent years. This literature has been largely dominated by sociologists, psychologists and public health specialists, although it is an area of growing interest to economists as well. A fundamental methodological problem with work in this area is that there are many unobserved characteristics of individuals that are expected to be related to self-reported mental health. Ignoring these factors may confound empirical estimates of the causal effects of observed variables like income, job status, health and education.* Recently, some researchers have addressed this issue and have advocated the

* **Correspondence to:** Antonio R. Andrés, Department of Economics, University of Southern Denmark, Campusvej 55, 5230 Odense, Denmark
Tel.: +45-6- 550 2077
Fax: +45-6- 615 8790
E-mail: ara@sam.sdu.dk
Source of Funding: None declared

* As noted recently, the issue of reverse causality is a serious concern. See, for example, Meer *et al.*[2] and Adams *et al.*[3]

Copyright © 2004 ICMPE

use of panel (or longitudinal) data. This type of data are able to control for unobserved factors if they are time invariant, whereas a cross-section study or time series study cannot. In our context, these factors might include family background, lifestyles, and health endowment (abilities, investment by parents). For instance, a person's disposition, personality or life style may influence his/her level of reported psychological well-being, so we would expect that a person inherently happier will have better self-reported mental health scores than a person who is identical in every respect but has depressive tendencies. But personality, disposition, or life styles are not observed in the data. These unobserved individual characteristics may be correlated with the observed determinants of self-reported mental health and omitting them causes bias in the estimation. Where this study differs from most of the existing work is that it explicitly addresses the issue of causality and it controls for important covariates like self-reported health status and education in contrast to Wildman & Jones,[4] and Wildman.[5]

The aim of this study is to examine the determinants of self-reported mental health in the UK. For that purpose, we apply an econometric method proposed by Hausman & Taylor.[6] This technique controls for time-invariant individual specific unobserved characteristics and enables the researcher to estimate the effect of time invariant variables. In particular, we are interested in assessing the effect of education on mental health which other studies have neglected.*

We use data from the first eight waves of the British Household Panel Survey (BHPS). The BHPS provides detailed information on income, and socio-demographic characteristics of individuals as well as on health. Static regression models are estimated separately for men and women as in Wildman & Jones,[4] Wildman,[5] and Clark.[8]

Determinants of Self-Reported Mental Health

A large body of the empirical literature has found consistent links between a number of socio- economic and demographic variables and self-reported mental health.† These include unemployment, self-reported health status, gender, age, and marital status. In this section, our main objective is to review the empirical findings in the economic literature on self-reported mental health.

Income

The relationship between income and self-reported mental health is not clear-cut. Though some studies indicate that self-reported mental health has a positive association with income,[10-12] there are many studies suggesting that the relationship is nonexistent.[4,5,8,13,14] Further, recent studies have argued that it is individual's ''relative'' rather than ''absolute'' income that relates to self-reported mental health.[4,5,15-18]* However, the direction of causality between income and health is open to debate. Causality might run in both directions. Whilst individuals with higher income may have better access to mental health care services or have better level of health knowledge, it is also the case that with good mental health, people are more likely to be economically productive and have higher incomes.[20,21] Alternatively, individuals with a low rate of time preferences may undertake investments in human capital as well as engage in behaviors that improve their prospective health.[22] Finally, it has been suggested that income and health may be jointly determined by unobservable time invariant factors, such as prior experiences or life events.[23,24]

Unemployment

Research by economists has also confirmed the adverse impact of unemployment on self-reported mental health.[8, 11,13,14,25] This result can be explained by recognizing that joblessness may lead to depressive episodes, anxiety, loss of confidence, self-esteem, reducing psychological well-being levels. Often, it has been ignored in the formal literature that causality may run from mental health to unemployment. People with lower psychological health are more likely to work less and therefore exit out the labor market early. As Fuchs[26] indicates, health and unemployment may be also associated through unobserved individual characteristics. New empirical evidence of these relationships from longitudinal data can be found in Hamilton *et al.*[27] for Canada; Kerkhofs & Lindeboom[28]; and Lindeboom *et al.*[24] for the Netherlands.

Individual Characteristics

A wide range of individual characteristics are also considered to be important predictors of self-reported mental health. The economic literature on self-reported mental health reports evidence that self-reported mental health is U-shaped in age.[8,11,13,14,29] In addition, Wildman & Jones,[4] using data from the first seven waves of the BHPS, identified there was a U-shape relationship between age and self-reported mental health for males but not for females.

Some studies document a positive relation between education and self-reported mental health.[8,10,11,30-32] By contrast, Clark & Oswald,[13] report a negative association. In addition, Theodossiou[14] finds education has no significant effect on self-reported mental health. However, these authors do no address the issue that education may be endogenous. Thus, a considerable degree of caution should be given to interpreting their findings as the true causal effect of education on mental health. There are two theoretical arguments, why education may not be exogenous. First, when those with higher ability obtain more education and when those with a high health endowment are healthier as adults, any positive

* Similar approach is used in Contoyannis & Rice.[7] In particular, they examine the impact of self-assessed health status on wages using six waves of the British Household Panel. Their results confirm that poor health status reduces the hourly wage for males, whilst excellent health status increases significantly the hourly wage for women.

† The pioneering studies on well-being were developed in the mid of 1970's. See Easterlin.[9]

* Psychologists also stress the importance of relative position in an individual's assessment of their well-being. See, for instance, Diener.[19]

Copyright © 2004 ICMPE

correlation between ability and health endowment will imply a positive association between education and health. These will imply biases if not taken into account. Second, those individuals with lower discount rate (higher education) will more likely to engage in health investments.[26] In this case, the relationship between health and education is artificial, an individual's discount rate will affect both education and health choices.

It has also been found that marriage improves psychological well-being over being single and that the experience of divorce or marital dissolution significantly worsen it.[4,5,8,12-14]

Ethnicity has been used in mental health studies as an additional factor that may influence self-reported mental health. For instance, Shields and Wailoo,[32] using the Fourth National Health Survey of Ethnic Minorities (FNHEM),* document that both black Caribbean and South Asian men report lower levels of well-being or happiness than Whites. Wildman and Jones,[4] using data from the first eight waves of the BHPS, do not find a significant effect of ethnicity on self-reported mental health scores.

There also appears to be that psychological well-being is enhanced by having children.[5,31] Clark & Oswald,[13] Gerdtham & Johannesson,[11] and Theodossiou[14] find a negative relationship between the well-being scores and number of children. Wildman and Jones[4] fail to find empirical evidence that the number of children either ameliorates or deteriorates an individual's self-reported mental health.

Self-assessed Health

Finally, binary measures of self-reported health status† (excellent or good health) have been found to be powerful predictors of mental health. In general, physical health measures (good or excellent) are associated with higher levels of psychological health.[8,11,13] However, one has to be careful about extracting some conclusions since health status might be endogenous in well-being equations. More specifically, there could be certain characteristics of individual that might be correlated with self-reported mental health and/or health status (for instance, health endowment, and life events).

In sum, no definite conclusion can be reached from the above empirical evidence. One of the weaknesses of this literature is that it relies on restrictive assumption of exogeneity of some variables such as education, self-assessed health, income and job status. In this paper, an instrumental variable estimator is applied which allows for the relaxation of the exogeneity assumption.

Methods

Our empirical model of mental health is based on those found in existing literature on self-reported mental health.[4,5,8] In general, the self-reported mental health score is a linear function of individual characteristics, self-assessed health, household composition and a set of socio-economic variables. Formally, the equation to be estimated is:

$$GHQ1_{it} = X'_{it}\beta + Z'_i\gamma + \varepsilon_{it}$$
$$i = 1, \ldots, N. t = 1, \ldots, T. \quad (1)$$

where $GHQ1_{it}$ is the reported mental health score of individual i at time t, X_{it} is a vector of time varying regressors, and Z_i represents a vector of time-invariant regressors. The error term, ε_{it}, defined as:

$$\varepsilon_{it} = \eta_i + v_{it} \quad (2)$$

contains an individual specific component, η_i, primary which is constant over time, and an idiosyncratic error term v_{it}, with mean zero and constant variance σ^2_v. The coefficients to be estimated are called β and γ.

Estimation Issues

It is very likely that the included explanatory variables (education, health status and job status) are correlated with η_i.* If this is the case, ordinary least squares (OLS) and generalized least squares (GLS) on [1] will yield biased and inconsistent estimates of all the parameters while the within (or fixed effect) estimator that removes the individual specific effects η_i yields unbiased estimates of β.† However, the latter estimator also eliminates the vector Z_i and as a consequence γ cannot be directly estimated. In our application, we could not obtain estimates for the education or ethnicity variables.

A consistent and potentially more efficient alternative to the fixed effects formulation is Hausman and Taylor's[6] instrumental variables procedure (HT).* Here, the variables which are correlated with the individual specific effects, (*endogenous*) are separated from uncorrelated variables (*exogenous*). The HT estimator is equivalent to run pooled two stage least squares on the same data transformation required for the random effects approach with the time means of the time-varying exogenous regressors and deviations from the group means of the time-varying endogenous regressors as legitimate instruments.†

Crucial for this estimator to be consistent is the correct partition of variables in subsets of exogenous and endogenous variables. The appropriateness of the partition can be tested by a Hausman type test of overidentifying

* The FNHEM is a cross-section survey collected between 1993 and 1994.

† There is a substantial literature on biases of subjective health measures. For instance, Bazzoli,[33] Bound,[34] and Kerkhofs & Lindeboom[35]. Other researchers argue that self-reported health measures are reliable; see Savoca,[36] Stern,[37] and Oswald.[38]

* It is assumed throughout the paper that the random term is uncorrelated with all regressors included.

† For more details, see, for instance, Baltagi.[39]

* This estimator was originally intended for a balanced panel. In Gardner,[40] this estimator is modified to handle unbalanced panels.

† Amemiya and MaCurdy,[41] and Breusch, Mizon & Schmidt,[42] developed similar estimators which are more efficient under certain conditions (see, Cornwell & Ruppert[43]).

Copyright © 2004 ICMPE

restrictions based on the difference between the within and HT estimates. While the within estimates are consistent under the null and alternative hypothesis, the HT is only consistent under the null hypothesis.*

Thus far, we have presented an econometric approach that can be used to get consistent and efficient estimates when some of the explanatory variables are correlated with the unobserved individual effects but not with the random term. As discussed above, for instance, health, job status, and income might also be correlated with the error term and this simultaneity bias is not necessarily time invariant. Nonetheless, one may argue that there may be a delay during which marital status, income and labor market status respond to mental health shocks. If this were so, these variables would be weakly exogenous and therefore their impact may be estimated without simultaneity bias.

Data

The specified empirical regression model outlined above is estimated separately for men and women using data from the British Household Panel Survey (BHPS). The BHPS is an annual panel survey covering a random sample of about 10,000 individuals in more than 5,000 households. The first wave of BHPS took place in 1991.† The same individuals are followed and re-interviewed in each subsequent wave, if they leave their original households to form a new one, all adult members of these new households are also interviewed. Similarly, children in original households are interviewed when they are sixteen. The primary advantage of the BHPS is that it contains detailed information on individual and household demographics, health, job related characteristics, values and finances on an annual basis.

For estimation, we focus on the sample of individuals who had given a full interview from waves 1 to 8.* In addition, we excluded individuals who had missing values on the variables of interest. After these selections, we come up with a working sample of 5222 individuals, 2321 men and 2901 women.†

Dependent Variable

The measure of self-reported mental health used is the General Health Questionnaire (GHQ) 12 score developed by Goldberg and Williams.[45] The GHQ score is a reliable measure for psychological well-being or mental disorders.[46]* It is based on answers to 12 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 day to day activities, ability to face problems, loss of confidence, self-worth, general happiness and whether suffering depression. Respondents rate each question on a three-point scale, ranging from 0 to 3 (the best score). A Likert[47] scale is used to construct an overall score for each individual by summing the responses to the 12 questions. Thus, our mental health variable (GHQ1) ranges from 0 to 36. The lowest level of self-reported mental health corresponds to a GHQ1 score of 36.

Independent Variables

The measure of income employed in this paper is the equivalised and deflated annual household income. To account for differences in household size, we transform the total household income into equivalent incomes by dividing by the square root of the number of household members. It is also deflated to 1991 prices using the retail price index. The log of income (LNY) is used to allow for concavity in the mental health-income relationship, as found in previous work.[48,49]

Other explanatory variables included in the model are marital status (DIVSEP (divorced or separated), WIDOWED (widowed) and NVRMAR (never married), an indicator of ethnicity (NON-WHITE), the educational level achieved during the sample period (DEGHDEG (degree or higher qualifications), HNDALEV (HND or A-level), OCSE (O-level or CSE qualification),† the number of individuals in the household including the respondent (HHSIZE) and number of children in the household at different ages (NCH04, NCH511 and NCH1218). A full list of job status variables is included as proxy to social status. The categories included are: SELFEMP (self-employed), UNEMPL (unemployed), RETIRED (retired), FAMCARE (family carer), LTSICK (long term sickness and disabled), MATLEAVE (maternity leave, for women only), and STUDENT (school student). We also allow for a flexible relationship between the respondent's age and GHQ1 score by including a cubic polynomial in age (AGE, AGE2, and AGE3) as in Wildman & Jones,[4] and Wildman.[5] Finally, we also include two binary variables concerning to the self-reported health status of the respondents corresponding to excellent (SAHEX) and good health (SAHGOOD).

In the current application, we treated (DEGHDEG, HNDALEV, and OCSE) as *endogenous time invariant variables,* (NONWHITE) as *exogenous time invariant variable*, (SELFEMP, UNEMP, RETIRED, FAMCARE,

* For more details, see Hausman and Taylor.[6]

† The initial selection of households for inclusion in the survey was performed using a two stage stratified sampling procedure designed to give each address the same probability of selection. For further details, see Taylor *et al.*[44]

* Hausman type tests based on the difference between the fixed effects estimator from the balanced and unbalanced panel, indicate the existence of sample selection for women but not for men. This is something that could be explored in further work.

† Attrition bias may arise in longitudinal data. It is however beyond the scope of this paper to correct for this selection problem. Although there does exist a number of studies estimating static well-being equations, only a few of these have examined issues of attrition bias. For instance, Wildman[5] finds no evidence of attrition bias using the first seven waves of the BHPS.

* 3,724 observations had missing values for the dependent variable.

† O (ordinary)-level and CGSE (General Certificate of Secondary Education) roughly correspond to a high school diploma; A (advanced) level corresponds beyond higher school but short of a university degree. Higher vocational degree consists of qualifications such as teaching and nursing qualifications, City and Guild certificates, Higher National Certificates/ Diploma and University Diploma.

Copyright © 2004 ICMPE

Table 1: Variable Definitions and Sample Means

Variable	Definition	Males	Females
GHQ1	Mental health indicator: General Health Questionnaire	10.30	11.68
LN Y	Log of annual household income	9.61	9.56
AGE	Age in years	45.53	46.28
HHSIZE	Number of people in household including respondent	2.89	2.80
WIDOWED	Marital status indicator: 1 = Widowed	0.03	0.10
DIVSEP	Marital status indicator: 1= Divorced or separated	0.05	0.08
NVRMAR	Marital status indicator: 1= Never married	0.17	0.12
DEGHDEG	Education indicator: 1 = Degree or higher degree	0.14	0.10
HNDALEV	Education indicator: 1 = HND or A-level qualification	0.28	0.20
OCSE	Education indicator: 1 = O-level or CSE qualification	0.27	0.33
NCH04	Number of children in household aged 0-4 years	0.15	0.16
NCH511	Number of children in household aged 5-11 years	0.26	0.30
NCH1218	Number of children in household aged 12-18 years	0.19	0.20
NONWHITE	Ethnicity indicator: 1= non-white	0.03	0.02
SELFEMP	Job status indicator: 1= self employed	0.13	0.04
UNEMP	Job status indicator: 1=unemployed	0.06	0.02
RETIRED	Job status indicator: 1= retired	0.17	0.19
STUDENT	Job status indicator: 1= school student	0.02	0.02
LTSICK	Job status indicator: 1= long term sick or disabled	0.04	0.02
MATLEAVE	Job status indicator: 1= on maternity leave	-	0.03
FAMCARE	Job status indicator: 1= family carer	0.01	0.16
SAHEX	Self-reported health indicator: 1= excellent	0.28	0.22
SAHGOOD	Self-reported health indicator: 1= good	0.48	0.49

STUDENT, LTSICK, SAHEX, SAHGOOD, LNY) as *endogenous time variant variables*, (AGE AGE2 AGE3, DIVSEP, NVRMAR, HHSIZE, NCH04, NCH511, NCH1218) as *exogenous time variant variables*.*

Definitions and sample means of variables used in the empirical analysis appear in **Table 1**. In general, men report better mental health (lower GHQ1 scores) than women. Also, men are slightly younger and belong to households with larger size and income. They are more likely to be single, have higher academic qualifications and are more likely to be unemployed and less likely to be widowed, divorced or separated.

Results

The results from applying the panel data estimators outlined above for the male and female samples are presented in **Table 2**. The first column shows the estimation results from generalized least squares. In the second column, within estimation results are reported. The third column displays the Hausman & Tailor estimation results. The test for individual effects is significant in every panel data model estimated (males: F-test = 5.71 (*p-value = 0.000*) and females: F-test= 5.01 (*p-value= 0.000*). Also, Hausman specification tests[50] reveal that the unobserved determinants of mental health are likely correlated with the explanatory variables (see **Table 2**).

For the time being, we discuss the consistent but inefficient within estimates. Being widowed, single, divorced or separated significantly increases ill-health for males. For females, the NVRMAR coefficient is negative and insignificant. Income appears to be associated with lower well-being, for males, although its coefficient (0.076) is close to zero. As can be seen, the opposite effect is found for females. Also, in the case of females, the estimate coefficient on LN Y is close to zero (-0.049). As expected, we find strong effects of health variable. Self-reported mental health improves with physical health for both males and females.

The estimates also reveal a significant association between age and GGQ1 scores for males but not for females. Both quadratic and cubic terms appear to be strongly significant. This implies that mental health deteriorates with age at a

* For women, we treated NCH04, NCH511, NCH1218 as endogenous time variant variables and left everything else the same as in the men specification.

Copyright © 2004 ICMPE

Table 2. Estimation Results. Dependent Variable: GHQ1

Covariates	Generalized least squares		Within		Hausman - Taylor	
	Males	Females	Males	Females	Males	Females
NONWHITE	0.380	-0.159	——	—	1.050	0.108
	(1.00)	(0.42)			(1.82)	(0.11)
WIDOWED	1.155	1.153	1.487	2.066	1.235	1.865
	(3.76)	(5.98)	(3.67)	(7.41)	(3.71)	(7.28)
DIVSEP	1.515	1.197	1.940	1.034	1.678	1.086
	(7.56)	(7.22)	(7.89)	(4.85)	(7.75)	(5.38)
NVRMAR	0.378	0.163	0.727	-0.065	0.555	-0.06
	(2.48)	(1.00)	(3.72)	(0.29)	(3.23)	(0.28)
HHSIZE	0.066	0.008	0.04	0.057	0.03	0.053
	(1.36)	(0.15)	(0.73)	(0.94)	(0.57)	(0.89)
AGE	0.607	0.495	0.58	0.292	0.565	0.268
	(8.59)	(6.92)	(5.88)	(2.82)	(6.91)	(2.67)
AGE2	-1.173	-0.937	-1.095	-0.408	-1.038	-0.343
	(7.92)	(6.34)	(5.16)	(1.86)	(5.80)	(1.63)
AGE3	0.692	0.520	0.646	0.207	0.603	0.159
	(7.11)	(5.48)	(4.58)	(1.45)	(5.12)	(1.18)
SELFEMP	-0.048	0.417	-0.095	0.222	-0.095	0.222
	(0.37)	(2.08)	(0.58)	(0.95)	(0.59)	(0.232)
UNEMP	1.935	1.42	2.018	1.32	2.007	1.317
	(13.08)	(6.51)	(12.90)	(5.86)	(12.91)	(0.224)
RETIRED	0.169	0.194	0.134	0.309	0.133	0.312
	(0.97)	(1.25)	(0.68)	(1.79)	(0.69)	(0.171)
MATLEAVE	—	0.393	—	0.604	—	0.596
		(2.20)		(3.22)		(3.20)
FAMCARE	1.007	0.533	0.95	0.573	0.943	0.128
	(3.21)	(4.67)	(2.90)	(4.46)	(2.91)	(4.46)
STUDENT	1.056	-0.014	1.07	0.029	1.067	0.03
	(4.29)	(0.06)	(4.13)	(0.11)	(4.14)	(0.12)
LTSICK	2.836	2.11	2.41	1.763	2.382	1.765
	(13.01)	(8.59)	(9.69)	(6.37)	(9.64)	(6.41)
DEGHDEG	0.288	-0.06	——	——	-1.883	6.054
	(1.33)	(0.25)			(1.04)	(1.59)
HNDALEV	-0.04	-0.269	——	——	3.062	-5.974
	(0.23)	(1.48)			(1.45)	(1.11)
OCSE	-0.124	-0.208	——	——	1.654	12.068
	(0.71)	(1.32)			(0.84)	(3.68)
NCH04	-0.124	0.182	-0.055	0.108	-0.054	0.110
	(1.26)	(1.81)	(0.51)	(0.97)	(0.52)	(1.00)
NCH511	0.02	-0.07	0.072	-0.184	0.079	-0.186
	(0.26)	(0.88)	(0.80)	(1.96)	(0.90)	(2.01)
NCH1218	0.045	0.025	0.09	-0.114	0.102	-0.118
	(0.53)	(0.29)	(0.98)	(1.20)	(1.16)	(1.25)
SAHEX	-2.39	-3.007	-1.79	-2.289	-1.78	-2.29
	(23.65)	(29.65)	(16.18)	(20.45)	(16.21)	(20.61)
SAHGOOD	-1.62	-2.03	-1.26	-1.578	-1.26	-1.579
	(19.20)	(25.86)	(14.03)	(18.84)	(14.08)	(18.98)
LN Y	0.034	-0.131	0.076	-0.049	0.083	-0.045
	(0.48)	(1.89)	(0.96)	(0.62)	(1.06)	(0.58)
Hausman test			$\chi^2(19)$=233.86	$\chi^2(2)$=365.12		
(p-value)			(0.0000)	(0.000)		
Overidentifying test					$\chi^2(7)$=9.55	$\chi^2(4)$=5.30
(p-value)					(0.2155)	(0.2578)

Notes: Absolute *t* values in parentheses. An intercept is included in all regressions. Estimates were performed using STATA v.8.

Copyright © 2004 ICMPE

decreasing rate. The estimated effects of job status variables are consistent one would expect. Being unemployed, maternity on leave, long term sickness or disability increases significantly mental distress; there is no significant effect for retired. The largest impact on GHQ scores comes from long term sickness or disability for both males and females. Consistent with other studies, the family structure has no significant impact on self-reported mental health. Those with children aged 5-11 years old in the household have better mental health, but this is only statistically significant for females.

As stated above, the within estimator has some potential defects. In order to derive the HT estimator, one has to distinguish which variables are correlated or uncorrelated with the individual specific effects. We now check the validity of the choice between exogenous and endogenous variables. The values of the Hausman test of overidentifying restrictions indicate that the HT estimator yields consistent and more efficient estimates in comparison with the fixed effects (or within) approach (see **Table 2**).*

Turning to the coefficients for the time invariant variables, individuals from a different ethnic group than white (although these coefficients are not statistically significant) are associated with worse mental health for both males and females. Of particular interest here is the effect of education on well-being. **Table 2** column (3) also reveals that there are large gender differences in relation to the effects of education self-reported mental health. For females, higher academic qualifications are positively correlated with self-reported mental health scores, as opposed to the case for men, although these effects are not significant. Interestingly, for females, the coefficient estimate on HNDALEV is negative and statistically significant, suggesting that subjective mental health is higher for those females with lower levels of education.

Conclusion

This study was based on individual data from the first eight waves of the British Household Panel Survey (BHPS). It made possible to examine the determinants of self-reported mental health in relation to a wide range of individual characteristics, health and socio-economic indicators in a large representative sample of the population of Britain. Estimation with instrumental variables panel data procedures allows us to account for the potential endogeneity of variables, such as education, health status, income and job status, related to mental health.

The results show no evidence that income impacts on self-reported mental health. Ethnicity is also found to worsen psychological well-being yet the effect is not significant. Marital status, age, job status and health had a significant impact on mental health scores. In addition, the effect of education differs across gender and seems to be larger for females than males. Consistent with what has been found in the literature on mental health, the results also suggest significant effects of low educational level on self-reported mental health only for females. In general, the results are usual in the empirical literature of mental health.

We believe that a deeper understanding of determinants of mental health and its gender differences is of great interest not only to academic world but also policy makers. Mental health policies need to recognize the importance of other areas of social and health services that have strong implications for mental health. Issues related to unemployment and social cohesion may have an important role in the prevention of mental illness, and policies aimed at improving these factors may have an impact on the mental health status of society. Also, as our results suggest, mental health policies for males and females should be differently implemented.

As with all longitudinal data, attrition bias may affect the results. In order to draw definite conclusions, it is important to formally test the presence of attrition bias as well as expand the sample to include more time periods. Still, we are concerned about the issue of weak correlation between the instruments and potential endogenous variables. Conventional specification tests detected this problem. As we know, when the instruments are weak, instrumental variables estimation exhibits large bias, even the sample size is large. Nevertheless, instrumental variables regressions do confirm the expected results. Additionally, we have to bear in mind that inconsistent estimates may potentially occur if the partition of the variables in subsets of endogenous and exogenous is not correctly specified. This issue needs to be explored further. This paper is a first step towards extending the formal literature to establish the true effects of socio-economic variables on self-reported mental health. The technique presented here can be applied to a wide range of health services research, for instance, models of impatient length of stay.[53]

Acknowledgements
Data from the British Household Panel Survey (BHPS) supplied by the ESRC Data archive. Neither original collectors of the data nor the Archive bear any responsibility for the analysis presented here. I would like to thank J.T. Lauridsen, and J. Roberts for helpful comments on an earlier draft. Financial support by the University of Southern Denmark is gratefully acknowledged

References

1. The Mental Health Foundation. http://www.mentalhealth.org.uk [25/05/2004].
2. Meer J, Miller DL, Rosen HS. Exploring health-wealth nexus. *J Health Econ* 2003; **22**: 713-730.
3. Adams P, Hurd MD, McFadden D, Merril A, Ribeiro T. Healthy, wealthy, and wise? Tests for direct casual paths between health and socioeconomic status. *J Econom* 2003; **112**: 3-56.

* As with conventional instrumental variables approaches, we also test for weak instruments following Bound, Jaeger *et al.*[51] and Staiger & Stock.[52] Specification tests appear to have low power. Results are available from the author on request.

Copyright © 2004 ICMPE

4. Wildman J, Jones AM. *Is it absolute income or relative deprivation that leads to poor psychological well-being? A test based on individual longitudinal data*. ECuity Working Paper 2002.
5. Wildman J. Income related inequalities in mental health in Great Britain: analysing the causes of health inequality over time. *J Health Econ* 2003; **22**: 295-312.
6. Hausman J, Taylor WE. Panel data and unobservable individual effects. *Econometrica* 1981; **49**: 1377-1398.
7. Contoyannis P, Rice N. The impact of health on wages: Evidence from the British Household Panel Survey. *Empir Econ* 2001; **26**: 599-622.
8. Clark AE. Unemployment as a social norm: psychological evidence from panel data. *J Labor Econ* 2003; **21**: 323-351.
9. Easterlin R. Does economic growth improve the human lot?. In *Nations and Households in Economic Growth*. David PA and Reder MW (eds). New York and London: Academic Press, 1974.
10. Clark A, Georgellis Y, Sanfrey P. Scarring: the psychological impact of past unemployment. *Economica* 2001; **68**: 221-241.
11. Gerdtham UG, Johannesson M. The relationship between happiness, health and socio-economic factors: results based on Swedish microdata. *Journal of Socio Economics* 2001; **30**: 553-557.
12. Winkelman L, Winkelman R. Why are the employed so unhappy? Evidence from a panel data. *Economica* 1998; **65**: 1-15
13. Clark AE, Oswald AJ. Unhappiness and unemployment. *Economic Journal* 1994; **104**: 648-659.
14. Theodossiou I. The effects of low-pay and unemployment on psychological well-being: A logistic regression approach. *J Health Econ* 1998; **17**: 85-104.
15. Clark AE, Oswald AJ. Satisfaction and comparison income. *J Public Econ* 1996; **61**: 359-381.
16. Daly M, Duncan G, Kaplan G, Lynch J. Macro-to-Micro links in the relationship between income inequality and mortality. *Milbank Q* 1998; **76**: 315-339.
17. Frank RH. *Choosing the right pond: Human Behavior and the Quest for Status*. London: Oxford University Press, 1985.
18. Kennedy BP, Kawachi I, Glass R, Prothrow-Stith D. Income distribution, socioeconomic status and self rated health status in the United States: multilevel analysis. *Br Med J* 1998; **317**: 917-921.
19. Diener E. Subjective well-being. *Psychol Bull* 1984; **95**: 542-575.
20. McClellan M. Health events, health insurance, and labor supply: evidence from health and retirement survey. In *Frontiers in the Economics of Aging*. Wise DA (ed). University of Chicago Press, Chicago, 1998; 301-346.
21. Wu S. The effects of health events on the economic status of married couples. *J Hum Resour* 2003; **38**: 219-230.
22. Barsky RB, Juster FT, Kimball MS, Shapiro MD. Preference parameters and behavioral heterogeneity: an experimental approach in the health and retirement study. *Q J Econ* 1997; **112**: 537-579.
23. Elder GH, Liker JK. Hard times in women's lives: Historical influences across forty years. *American Journal of Sociology* 1982; **88**: 241-269.
24. Lindeboom M, Portrait F, van de Berg GJ. An econometric analysis of the mental health effects of major events in the life of older individuals. *Health Econ* 2002; **11:** 505-520.
25. Korpi T. Is utility related to employment status?, Employment, unemployment, labour market policies and subjective well-being among Swedish youth. *Labour Economics* 1997; **4**: 125-147.
26. Fuchs VR. Time preference and health: an exploratory study. In *Economic Aspects of Health*. Fuchs VR. (ed). Chicago: Chicago University Press, 1982; 93-120.
27. Hamilton VH, Merrigan P, Dufresne E. Down and out: estimating the relationship between mental and unemployment. *Health Econ* 1997; **6**: 397-406.
28. Kerkhofs M, Lindeboom M. Age health related dynamics and changes in labor market status. *Health Econ* 1997; **6**: 407-423.
29. Clark AE, Oswald AJ, Warr PB. Is job satisfaction U-shaped in age?. *Journal of Occupational and Organizational Psychology* 1996; **69**: 57-81.
30. Warr P. Age and occupational well-being. *Psychol Aging* 1992; **7**: 35-45.
31. Shields MA, Price SW. *Exploring the economic and social determinants of psychological and psychosocial health*. IZA Discussion Paper No. 396 2001.
32. Shields MA, Wailoo A. Exploring the determinants of unhappiness for ethnic minority of men in Britain. *Scott J Polit Econ* 2002; **49**: 445-466.
33. Bazzoli G. The early retirement decision: new empirical evidence on the influence of health data. *J Hum Resour* 1985; **20**: 214-234.
34. Bound J. Self-reported versus objective measures of health in retirement models. *J Hum Resour* 1991; **26**: 107-137.
35. Kerkhofs M, Lindeboom M. Subjective health measures and state dependent reporting errors. *Health Econ* 1995; **4**: 221-235.
36. Savoca E. Controlling for mental health in earning equations: What do we gain and what do we lose?. *Health Econ* 1995; **4**: 399-410.
37. Stern S. Measuring the effect of disability on labor force participation. *J Hum Resour* 1989; **24**; 361-395.
38. Oswald AJ. Happiness and economic performance. *Economic Journal* 1997; **107**: 1815-1831.
39. Baltagi B. *Econometric Analysis of Panel Data*, 2nd edition. John Wiley & Sons, 2001.
40. Gardner R. Unobservable individual effects in unbalanced panel data. *Econ Lett* 1998; **58**: 39-42.
41. Amemiya T, MaCurdy TE. Instrumental variable estimation of an error components model. *Econometrica* 1986; **54**: 869-880.
42. Breusch TS, Mizon GE, Schmidt P. Efficient estimation using panel data. *Econometrica* 1989; **57**: 695-700.
43. Cornwell C, Rupert P. Efficient estimation with panel data: An empirical comparison of instrumental variables. *Journal of Applied Econometrics* 1998; **3**: 149-155.
44. Taylor M, Brice J, Buck N, Prentice E. *British household panel survey user manual*. Volume A: Introduction, technical report and appendices. University of Essex, Colchester, 1998.
45. Goldberg D, Williams P. A user's guide to the General Health Questionnaire. NFER-Nelson: Windsor, 1988.
46. Argyle M. *The Psychology of Happiness*. London: Routledge, 1989.
47. Likert R. A technique for the development of attitude scales. *Educ Psychol Meas* 1952; **12**: 313-315.
48. Ettner SL. New evidence on the relationship between income and health. *J Health Econ* 1996; **15**: 67-85.
49. Ecob R, Davey Smith G. Income and wealth: what is the nature of the relationship?. *Soc Sci Med* 1999; **48**: 693-705.
50. Hausman J. Specification tests in econometrics. *Econometrica* 1978; **49**: 1377-1398.
51. Bound JD, Jaeger DA, Baker R. Problems with instrumental variables estimation when the correlation between the instruments and the endogenous explanatory variable is weak. *J Am Stat Assoc* 1995; **90**: 443-450.
52. Staiger D, Stock JH. Instrumental variables regressions with weak instruments. *Econometrica* 1997; **65**: 557-586.
53. Lindrooth, RC, Hoerger TJ, Norton EC. Expectations among the elderly about nursing home entry. *Health Serv Res* 2000; **35:** 1181-1202.

Copyright © 2004 ICMPE