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Persistence in health limitations: a European comparative analysis

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Abstract. This paper investigates the persistence in health limitations for individuals within the member states of the European Union. We use the full 8 waves of data available in the European Community Household Panel (ECHP) to explore the relative contributions of state dependence, unobserved heterogeneity and socioeconomic characteristics, in particular income, education and activity status, and how these vary across countries. We focus on binary measures of health limitations, constructed from the answers to the question: "Are you hampered in your daily activities by any physical or mental health problem, illness or disability?". Dynamic non-linear panel data models are specified and estimated using both pooled and random effects probit and logit models together with complementary log-log models. The random effects probit specifications are preferred. Results reveal high state dependence of health limitations which remains after controlling for measures of socioeconomic status. There is heterogeneity in the socioeconomic gradient across countries.

Keywords: health limitations, dynamic models, panel data
JEL codes: I12 C23

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1. Introduction

Health has long been considered a fundamental commodity and economic models have emphasised the inter-temporal aspects of health (see e.g., Grossman, 2000). While it is well known that health deteriorates with age and is a function of socioeconomic status (SES), the exact nature of the link between SES and health remains unclear. The fact that individuals with greater wealth, better education and higher occupational status tend to live longer and enjoy better health does not imply the direction of causality and the extent to which SES impacts on health and health status impacts on SES. Persistent differences in health by SES are one of the key policy issues facing many European countries where concern exists over the level of inequalities in health and health care use, particularly as a result of the expansion of the European Union and the ageing of its populations (see e.g. Kunst et al., 2004; van Doorslaer and Jones, 2004; van Doorslaer and Koolman, 2004).

Empirical analyses of the determinants of health have attempted to address concerns of causality, most recently by focusing on the analysis of longitudinal data where individuals can be followed over time, such that the timing of changes in SES and changes in health status can be observed (Adams et al., 2003; Arendt, 2005; Buckley et al., 2004; Contoyannis et al., 2004a, 2004b; Frijters et al., 2005; Halliday, 2005; Hurd and Kapteyn, 2003; Jensen and Richter, 2003; Jones et al., 2006; Kerkhofs and Lindeboom, 1997; Lindahl, 2005; Meer et al., 2003; Salas, 2002). The temporal sequence of such events can be used to aid the identification of a causal link between SES and health[1]. Adopting a longitudinal perspective allows the investigation of health state dynamics, to address the question why some individuals experience persistently good health and others experience persistently poor health.

This paper compares the persistence of health limitations across countries within the pre-enlargement European Union (EU-15). Using panel data methods we exploit the full 8 waves of available data from the European Community Household Panel User's

[1] Some studies have attempted to identify exogenous variation in income through 'natural experiments' such as the macroeconomic shocks associated with the pensions crisis in Russia (Jensen and Richter, 2003) and the reunification of Germany (Frijters et al., 2005), lottery winnings (Lindahl, 2005) or inherited wealth (Meer et al., 2003) or exogenous variation in education through educational reforms (Arendt, 2005).

Database (ECHP-UDB). The main objective of the study is to quantify the socioeconomic determinants of health limitations, in particular the contribution of income, education and labour market status, as well as the level of state dependence and unobserved heterogeneity and how these vary across member states of the European Union. To this end, we specify dynamic non-linear panel data models and estimate these with national data.

2. The dynamics of health

Recent analyses of health outcomes across European countries have focused on the distribution of health and health care and how inequalities are related to SES (e.g. Kunst et al., 2004; van Doorslaer and Koolman, 2004; van Doorslaer, Koolman and Jones, 2004). Evidence on income-related inequalities in health limitations has been provided at the EU-15 level using data from the ECHP-UDB (Hernández-Quevedo *et al*., 2006). The methods applied used a longitudinal perspective allowing both short- and long-run measures of inequalities to be computed. These inequalities favour richer individuals in each society.

Empirical analyses of health dynamics aim to address the question: why do some individuals experience persistently good health and others experience persistently poor health? To some extent this may reflect the nature of health problems: some illnesses are inherently chronic and long-lasting. Also a cumulative history of a range of health problems may have a direct influence on current health and on the effectiveness of medical care. These effects can be thought of as pure dynamics, often termed state dependence. But health problems may be persistent for other reasons; an individual may have individual or socioeconomic characteristics that predispose them to poorer health and that linger over time. Factors such as education, material deprivation, childhood nutrition and environment may have a long-lasting influence on an individual's health. Some of these factors may be observable, but others - such as ability, time preference and risk aversion - may be hard to control for.

These issues are exemplified by the debates over the association between health and socioeconomic status (SES): in particular health and education (see e.g., Arendt, 2005; Grossman, 2000; Smith, 2004) and health and income or wealth (see e.g., Buckley et al., 2004; Deaton and Paxson, 1998; Ettner, 1996; Frijters et al., 2005; Hurd and Kapteyn, 2003; Jensen and Richter, 2003; Lindahl, 2005; Meer et al., 2003; Smith, 1999, 2004; van Ourti, 2003). Evidence of a positive association between health and SES is well-documented across many societies and periods (see e.g. Smith, 1999; Deaton, 2003), but the causal mechanisms underlying this relationship are complex and controversial. There can be a direct causal link from SES to health, for example, through the direct influence of material deprivation on the production of health and on access to health care or of education on the uptake and compliance with medical treatments. There can be a direct causal link from health to SES, for example, through the impact of health shocks on labour market outcomes such as unemployment, early retirement (Bound, 1991; Disney et al., 2006; Rice et al., 2006, Hagan et al., 2006) and earnings (Contoyannis and Rice, 2001). But there may also be pathways that link health and SES through "third factors", for example time preference rates, that do not imply any causal link.

Cross-sectional data are inherently limited when it comes to dealing with the potential for reverse causality, that may mask the identification of causality from SES to health, and for investigating relationships that are dynamic in nature and evolve over a period of time. In contrast, panel data offer richer information from which to identify such relationships by allowing the specification of more complex models including the appropriate recognition of the timing of events as they evolve, such that shocks to SES can be related to subsequent changes in health.

Several studies consider the relationship between income and health by adopting a longitudinal perspective (e.g., Adams *et al.*, 2003; Benzeval and Judge, 2001; Benzeval et al., 2000; Buckley et al., 2004; Frijters, et al., 2005; Hurd and Kapteyn, 2003; Jensen and Richter, 2003; Lindahl, 2005; Meer et al., 2003; Smith, 2004; van Ourti, 2003). Recent studies have contributed to a deeper understanding of the dynamics of health. Kerkhofs and Lindeboom (1997) analyse the impact of age and changes in labour market status and work history on changes in health using a Dutch panel survey (CERRA). Hauck and Rice

(2004) explore health mobility in the British Household Panel Survey (BHPS) by specifying a dynamic error components model for the GHQ measure of psychological well-being. Salas (2002) investigates the association between SES and health in older men and women in the BHPS. Buckley *et al.* (2004) consider the relationship between SES and health transitions in the older Canadian population. Contoyannis, Jones and Rice (2004b) study the determinants of a binary indicator of functional limitations using seven waves of the BHPS.

Three papers in particular have shaped the methods used here and they are now described in more detail. Contoyannis *et al.* (2004a) base their study on the British Household Panel Survey (BHPS), focusing on three issues. First, they investigate the relative contribution of state dependence and heterogeneity in explaining the dynamics of health. Secondly, they analyse whether there is evidence of health-related attrition in the sample and its consequence for analysis. Finally, they explore the relationship between SES (education and income) and self-assessed health (SAH). Dynamic pooled ordered probit models are used to investigate these issues. They perform variable-addition tests for attrition bias and apply inverse probability weighting to adjust for attrition when they estimate pooled models. They find evidence of health-related attrition in the data, but estimates of state dependence and of the SES gradient in health are not distorted by this attrition. Heterogeneity is found to account for around 30% of the unexplained variation in health and there is positive state dependence. A more detailed study of sample attrition is presented in Jones, Koolman and Rice (2006). Their study is particularly relevant here as they investigate health-related attrition in the context of the ECHP-UDB. While they find evidence of non-response related to health status, estimates of the impact of socioeconomic variables on health do not appear to be adversely affected.

Contoyannis, Jones and Rice (2004b) focus on the determinants of the indicator of functional limitations using seven waves of the BHPS. They analyse the dynamics of health and, in particular, decompose the persistence in the health outcome into the contributions of state dependence, heterogeneity and serial correlation. Their results find strong positive state dependence in the dynamic models, implying that health problems should be considered as a "dynamic phenomenon".

Halliday (2005) investigates the dynamics of a self-reported measure of health status in the US Panel Study of Income Dynamics (PSID). Two objectives are pursued: to understand better how to model health over the life-cycle and to quantify the extent to which unobserved heterogeneity and state dependence contribute to the determination of health. They consider four determinants of health: idiosyncratic risk (health shocks), ageing, state dependence and heterogeneity and allow for a flexible specification of health by considering age-varying state dependence and introducing heterogeneity in all parameters of the model. They find that models with simpler specifications of heterogeneity and state dependence are preferred to more sophisticated specifications and that both unobserved heterogeneity and state dependence play important roles as determinants of health. However, the magnitude of state dependence depends on both the individual's age and unobserved characteristics.

Our aim is to draw on previous literature by quantifying the socioeconomic gradient of health limitations, through a dynamic analysis that takes into account the panel nature of the data. To this end, we use the *European Community Household Panel Users' Database* (ECHP-UDB) which is a standardised annual longitudinal survey providing 8 waves (1994-2001) of comparable micro-data about living conditions in the pre-enlargement European Union Member States (EU-15). Our analysis focuses on two binary measures of health limitations, constructed from the answers to the question: "Are you hampered in your daily activities by any physical or mental health problem, illness or disability?".

3. The ECHP-UDB

The *European Community Household Panel Users Database* (ECHP-UDB) is a standardised annual longitudinal survey, designed and coordinated by the European Commission's Statistical Office (EUROSTAT). It provides up to 8 waves (1994 - 2001) of comparable micro-data about living conditions in the pre-enlargement European Union Member States (EU-15). The survey is based on a standardised questionnaire that involves annual interviewing of individuals aged 16 and older from a representative panel of households

(Peracchi, 2002). National Data Collection Units implemented the survey in each of the member countries. Approximately, 60,000 households, with 130,000 adults, were interviewed. The survey covers a wide range of topics including demographics, income, social transfers, individual health, housing, education and employment. The information provided in the ECHP-UDB can be compared across countries and over time, making it an attractive dataset for the purpose of our study.

The first wave included all EU-15 Member States with the exception of Austria and Finland. Austria joined in 1995 and Finland, in 1996. For the first three waves, the ECHP ran parallel to existing national panel surveys in Germany (GSOEP), Luxembourg (PSELL) and the United Kingdom (BHPS). From the fourth wave onwards, the ECHP samples were replaced by data harmonized ex-post from these three surveys. Hence, there were two versions of the ECHP database for Germany, Luxembourg and the United Kingdom. Although Sweden did not take part in the ECHP, the Living Conditions Survey[2] is included in the UDB.

For the purpose of this study, we have included in our analysis those Member States of the EU contained in the ECHP that have the full 8 waves of data available. These are: Belgium, Denmark, France, Greece, Ireland, Italy, Portugal, Spain and The Netherlands.

3.1 Sample and variables

We use a balanced sample of respondents, which has been constructed by including only those individuals from the first wave who were interviewed in each subsequent wave[3]. Table 1 shows the sample size for each country, for the whole sample and split by gender. For most countries, the sample size is between 20,000 and 50,000 observations.

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[2] Note however that the data for Sweden is not longitudinal as it has been derived from repeated cross-sections. We do not use data for Sweden, given that it does not share the panel structure of the data.

[3] Care should be taken when interpreting the results as the respondents in the balanced panel may not be representative of the full sample. Jones, Koolman and Rice (2006) provide evidence of health-related non-response in the ECHP but they also find that estimates of the association between health and socioeconomic status are robust with or without adjustments for non-response and when using the balanced or unbalanced panels.

Exceptions are Spain and Italy with both having notably larger samples and Denmark and Ireland with smaller samples than the other countries included in the analysis.

Table 1: Sample size for each country considered in the analysis

	BE	DK	FR	GR	IR	IT	NL	PT	SP
Men	10,808	9,776	26,936	23,224	10,512	36,840	16,928	26,960	27,712
Women	13,256	10,512	30,872	27,848	11,472	39,472	20,320	31,824	32,680
NT	24,064	20,288	57,808	51,072	21,984	76,312	37,248	58,784	60,392

Key: Belgium (BE); Denmark (DK); France (FR); Greece (GR), Ireland (IR), Italy (IT), Netherlands (NL); Portugal (PT); Spain (SP).

3.2 Health limitations

The ECHP-UDB contains information on health outcomes and health care utilisation. We use the information on health limitations, in particular responses provided to the question[4]: "Are you hampered in your daily activities by any physical or mental health problem, illness or disability?". Three possible answers are available for the respondent: "Yes, severely", "Yes, to some extent" and "No". In the ECHP-UDB, this information is provided for all countries and waves that we consider for our analysis[5]. We focus on two binary measures of health limitations that have been derived from the responses to the health limitations question. From these responses, two dummy variables are constructed. The first variable, labelled HAMP1, represents an indicator of suffering any limitations in daily activity (severe or to some extent) versus no limitations; the second variable (HAMP2) is an indicator of suffering severe limitations in daily activity. We refer to these variables as `any' and `severe' limitations in the following text. The fact that the indicators are defined in this way means that our econometric specifications can be interpreted in terms of a generalised ordered response model: with ordered categories severe limitation, some limitation and no limitation (see e.g., Terza, 1985, Hernández-Quevedo et al., 2007).

[4] The question is labelled PH003A in the ECHP-UDB.

[5] Although the question was asked similarly in all the countries where the data was available, the French case is an exception as the question was reworded for the full panel (1994 – 2001) from "… hampered by any chronic, physical or mental health problem, illness or disability?" to "Gêné par une maladie chronique, un handicap?".

3.3 Explanatory variables

Five variables represent marital status (*Widowed*, *Single*, *Divorced*, *Separated*) with *Married* as the reference category. Three indicators have been constructed to represent maximum level of education attained based on the International Standard Classification of Education (ISCED): *Tertiary* (Third level), *Secondary* (second stage of secondary level) and *Primary* (less than second stage of secondary education), with *Tertiary* being the reference category. The size of the household (*HHSize*) and the number of children in the household by age (*nch04*, *nch511*, *nch1218*) are also included in the analysis. The income variable is the logarithm of equivalised real income, adjusted using the Purchasing Power Parities (PPPs) and the Consumer Price Index (CPI). It is equivalised by the OECD-modified scale to adjust for household size and composition. There are six possible categories for activity status: *Self-employed*, *Unemployed*, *Retired*, *Housework* and *Inactive*, with *Employed* individuals being the reference case[6]. Individuals have been grouped by age and sex, with a man aged between 16 and 25 being the reference case. A vector of time dummies is also included in the analysis to capture any general time trend in each country. Table 2 provides a list of variables used in this study, with their sample mean and standard deviation.

[6] Those individuals who reported either "in education or training" or "in community or military service" as their main activity status have been considered as "employed" for this particular analysis.

Table 2: Variable labels and descriptions, with sample statistics for data pooled across countries

		Mean	Std. Dev.
HAMP1	1 if severely hampered or to some extent by health problem, 0 otherwise	0.199	0.399
HAMP2	1 if severely hampered by health problem, 0 otherwise	0.069	0.254
SEPARATED	1 if separated, 0 otherwise	0.009	0.095
DIVORCED	1 if divorced, 0 otherwise	0.037	0.191
WIDOWED	1 if widowed, 0 otherwise	0.077	0.266
SINGLE	1 if never married, 0 otherwise	0.206	0.404
SECONDARY	1 if second stage of secondary level education ,0 otherwise	0.332	0.471
PRIMARY	1 if less than second stage of secondary level, 0 otherwise	0.439	0.496
HH_SIZE	Number of people in household including respondent	3.161	1.488
NCH04	Number of children in household aged 0 - 4	0.143	0.418
NCH511	Number of children in household aged 5 - 11	0.266	0.598
NCH1218	Number of children in household aged 12 - 18	0.321	0.649
LOG INCOME	Log of equivalised total net household income (PPP & CPI)	8.128	2.558
AGE2635M	Men with age between 26 and 35	0.083	0.276
AGE3645M	Men with age between 36 and 45	0.097	0.296
AGE4655M	Men with age between 46 and 55	0.088	0.284
AGE5665M	Men with age between 56 and 65	0.082	0.275
AGE6675M	Men with age between 66 and 75	0.057	0.233
AGE7685M	Men with age between 76 and 85	0.019	0.138
AGE86M	Men with 86 years old or more	0.002	0.048
AGE1625F	Women with age between 16 and 25	0.046	0.209
AGE2635F	Women with age between 26 and 35	0.093	0.291
AGE3645F	Women with age between 36 and 45	0.107	0.309
AGE4655F	Women with age between 46 and 55	0.097	0.296
AGE5665F	Women with age between 56 and 65	0.082	0.275
AGE6675F	Women with age between 66 and 75	0.070	0.255
AGE7685F	Women with age between 76 and 85	0.029	0.169
AGE86F	Women with 86 years old or more	0.004	0.068
SELF-EMPLOYED	1 if self-employed, 0 otherwise	0.106	0.308
UNEMPLOYED	1 if unemployed, 0 otherwise	0.054	0.227
RETIRED	1 if retired, 0 otherwise	0.200	0.400
HOUSEWORK	1 if doing housework, looking after children or other persons, 0 otherwise	0.160	0.367
INACTIVE	1 if other economically inactive, 0 otherwise	0.025	0.157

4. Descriptive Analysis

Figure 1 presents the distribution of health limitations for all countries and shows that, in general, the distributions are similar across countries with the majority of individuals reporting no perceived limitations in daily activities.

Figure 1: Distribution of health limitations for each country

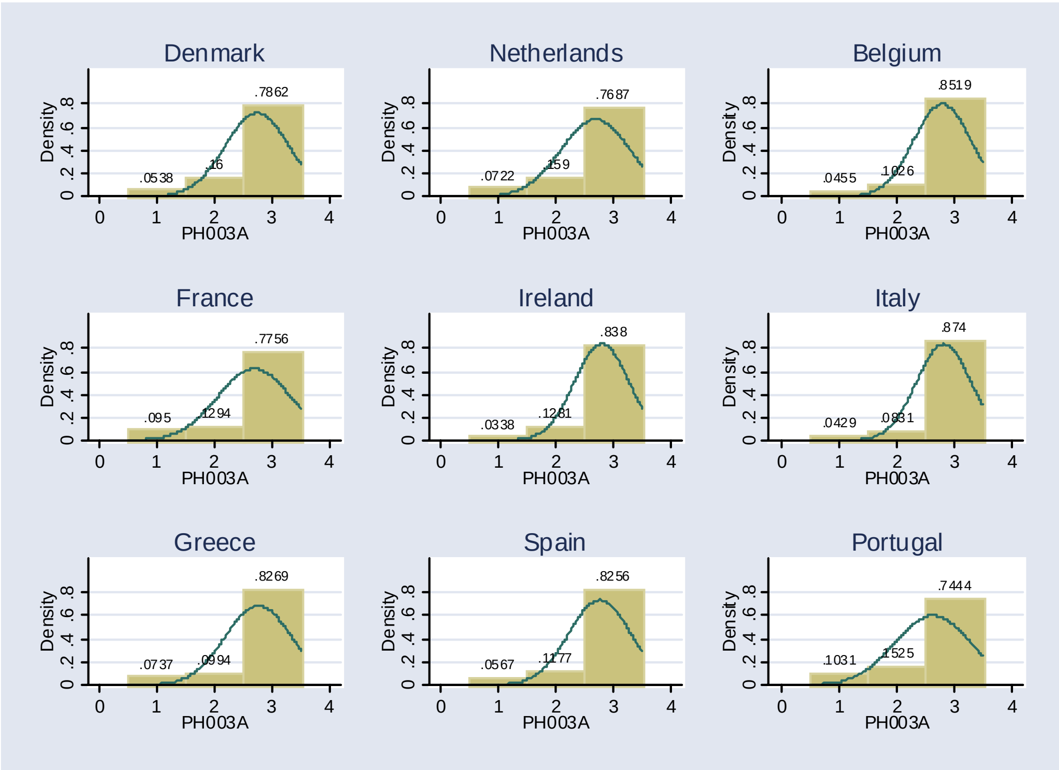

Table 3 shows the percentage of individuals who report either any or severe limitations across income quintiles. The results show clear evidence of gradients in reported health by income and by country. Minimum and maximum percentages are highlighted. These range from 6.3% of respondents who report some health limitations in the fifth income quintile in Italy to 20.4% in the first income quintile in Denmark. The range for severe health limitations is from 1.4% in the fifth quintile for Ireland to 15.4% in the second income quintile in Portugal. In general, there exists a gradient across income quintiles, such that a higher proportion of respondents in lower income quintiles report limitations compared to respondents from higher quintiles. Further, there is variation across countries in the observed income gradients. For example, for Portugal the gradient ranges from 15.4% of respondents reporting severe limitations in the second quintile to 5.5% in the fifth quintile. For Italy, the range is 5.2% in the first quintile to 2.7% in the fifth quintile.

Table 3: Percentage of health limitations by income quintiles

Country	Limitations to some extent					Severe limitations				
	Income quintiles					Income quintiles				
	1	2	3	4	5	1	2	3	4	5
Belgium	14.46	10.70	8.94	8.79	8.71	9.53	5.57	3.17	2.18	2.55
Denmark	20.38	17.54	16.64	13.81	11.23	10.75	7.12	3.43	2.67	2.08
France	16.69	15.01	12.98	10.18	10.18	14.11	11.90	10.52	5.65	5.65
Greece	14.39	11.81	9.73	9.50	6.43	12.26	9.44	7.55	6.51	3.49
Ireland	17.24	20.35	13.09	10.62	7.98	6.82	6.26	3.26	1.85	1.44
Italy	9.18	9.94	9.09	7.91	6.26	5.22	5.22	4.98	3.97	2.72
Netherlands	18.61	17.36	15.93	14.86	13.66	10.25	9.08	6.73	5.55	5.09
Portugal	19.35	18.53	15.53	14.25	11.14	14.30	15.36	11.34	8.43	5.50
Spain	14.71	15.51	13.44	10.49	7.01	7.23	7.36	7.08	5.38	2.59

Table 4 shows the distribution of health limitations by activity status and country. For respondents reporting severe limitations, the highest percentages correspond to those who report their activity status as retired. This is true for all countries with the exception of The Netherlands and Spain. For the former of these two, the highest reporting of limitations is found among individuals reporting their activity status as housework, and for the latter, among individuals that report inactivity. Similar results are found for the reporting of limitations to some extent, but whereas the distribution of severe limitations is, in general, concentrated within the retired, inactive or those involved in housework, we find high levels of reporting of some limitations among the employed. This is particularly the case for Denmark, The Netherlands, Belgium and France.

Table 4: Percentage of health limitations by activity status

Country	Limitations to some extent						Severe limitations					
	Activity status						Activity status					
	E	S	U	R	H	I	E	S	U	R	H	I
Belgium	29.24	3.89	6.57	40.31	14.09	4.58	12.98	2.47	7.95	49.82	13.15	13.25
Denmark	44.81	3.60	5.20	39.08	2.40	1.48	13.11	2.29	3.30	74.43	1.47	4.77
France	31.85	3.79	4.57	45.38	12.51	0.35	17.84	2.82	4.61	53.92	19.46	0.31
Greece	8.76	14.45	2.68	46.80	25.56	1.67	3.19	6.80	1.65	58.50	20.99	8.77
Ireland	15.90	9.27	4.58	21.33	35.68	11.89	7.80	4.57	2.55	27.15	26.08	31.18
Italy	18.39	8.23	3.75	41.79	22.44	4.08	7.97	4.22	2.57	49.22	22.91	12.68
Netherlands	35.47	2.88	8.48	2.94	36.03	11.88	23.45	1.61	11.76	2.81	40.10	18.77
Portugal	21.27	15.79	3.30	38.02	15.25	5.78	9.36	7.88	2.44	52.12	11.45	16.40
Spain	9.30	6.16	3.81	29.19	35.03	15.95	4.76	2.63	2.34	31.19	24.70	34.23

Note: 6 categories have been used to reflect activity status: employed (E), self-employed (S), unemployed (U), retired (R), housework (H) and inactive (I).

5. Econometric methods

This section develops multivariate models to explore in greater depth the relationship between SES and health while allowing for state dependence and individual heterogeneity. For each binary measure of health limitations we specify a binary response model with state dependence and individual heterogeneity in the following way[7]:

$$h_{it}^{*} = \alpha h_{it-1} + \beta x_{it-1} + \gamma z_i + \eta_i + \varepsilon_{it}, \qquad i = 1,\ldots,N; \quad t = 2,\ldots,T_i \tag{1}$$

In (1) h_{it}^{*} represents a latent variable representation of the observed level of health limitations; h_{it-1} is the lagged value of the health outcome, x_{it-1} is a vector of lagged values

[7] To reiterate the point made earlier, the way in which HAMP1 and HAMP2 are defined means that the combination of the two models can be interpreted as a generalised ordered response model, without the 'single index' assumption imposed on the model (see e.g., Terza, 1985, Hernández-Quevedo et al., 2007).

of the time-varying regressors, z_i is a vector of time invariant regressors, and η_i and ε_{it} represent a time-invariant individual-specific and an idiosyncratic error component respectively.[8] α, β and γ are conformable vectors of parameters to be estimated. The lagged value of health limitations is included in the specification to capture state dependence and to reduce concerns over previous health status impacting on current SES. This type of dynamic specification has been used extensively in the literature (see Adams *et al.*, 2003; Chay and Hyslop, 2000; Contoyannis, Jones and Rice, 2004a, 2004b; Salas, 2002 and Smith, 2004, 2005).

In our data the latent outcome, h_{it}^*, is not observed. Instead we observe a binary indicator of the category in which the latent indicator falls (h_{it}). The observation mechanism can be expressed as:

$$\begin{aligned} h_{it} &= 1, \text{ if } h_{it}^* > 0 \\ h_{it} &= 0, \text{ otherwise.} \end{aligned} \tag{2}$$

The estimation of dynamic models such as (1) poses particular problems, as identified by Heckman (1981). The first observation of our time series is clearly not the true initial outcome of the process we wish to study (the evolution of health), but instead simply represents the starting point of the ECHP survey. A further issue is that some of the observed set of regressors may be correlated with the individual unobserved effect. To allow for this possibility we parameterize the individual effect by including the first period observation of each regressor. This is in the spirit of including the within individual means of the time-varying regressors (Mundlak, 1978; Chamberlain, 1980; Wooldridge, 2005). Wooldridge (2005) provides a simple approach to deal with both correlated individual effects and the initial conditions problem in dynamic nonlinear models. It consists of modelling the distribution of the unobserved effect conditional on the initial value of both the health variable and exogenous variables. We implement this approach by parameterizing the distribution of the individual effects as:

[8] The dynamic models are estimated using data from waves 2-8 to accommodate the use of lagged variables.

$$\eta_i = \pi x_{i1} + \delta h_{i1} + \mu_i \quad (3)$$

where x_{i1} is the initial value of the exogenous variables and h_{i1} is initial observation of our health outcome. Accordingly, our full specification of model (1) is:

$$h_{it}^{*} = \alpha h_{it-1} + \beta x_{it-1} + \gamma z_i + \pi x_{i1} + \delta h_{i1} + \mu_i + \varepsilon_{it} \quad (4)$$

where $\alpha, \beta, \gamma, \delta,$ and π are parameters to be estimated.

We apply estimators appropriate for a binary response. The first is a probit specification, which in the case of the pooled model assumes that the distribution of $u_{it} = \mu_i + \varepsilon_{it}$ is $N(0,1)$ and for the random effects (RE) specification, assumes μ_i is distributed as $N(0,\sigma^2)$ and ε_{it} is distributed as $N(0,1)$. We further estimate the models by assuming the respective errors of the pooled and random effects specifications follow logistic and complementary log-log distributions. The complementary log-log distribution (CLL) is asymmetric and is typically used when the event of interest is rare.

Note that while the pooled models do not explicitly take account of the panel nature of the dataset, the estimator is a consistent estimator of the parameters of interest. Appropriate inference is achieved by using a robust estimator of the covariance matrix that allows for clustering within individuals. A feature of the pooled estimator is that it does not require the regressors to be strictly exogenous and can accommodate predetermined variables (see, for example, Wooldridge, 2002). This makes the estimator more robust in comparison to a random effects specification where strict exogeneity is assumed. Random effects models are estimated by Gauss-Hermite quadrature after checking for the adequacy of the number of points of support (see Butler and Moffitt, 1982).

We use both the Akaike and Bayesian Information Criteria (AIC and BIC) for model selection. The information criteria are log-likelihood based measures with differing degrees of freedom adjustments. They capture the trade-off between the model fit (measured by the maximised log-likelihood, *LnL*) and the principle of parsimony that favours a simple model. That is, they penalise model complexity. AIC and BIC are calculated as follows:

$$AIC = -2LnL + 2q$$
$$BIC = -2LnL + (LnM)q \tag{5}$$

where q represents the number of parameters in each specification and M ($= \sum_{i=1}^{N} T_i$) denotes number of observations. BIC applies a greater penalty than AIC for model complexity and hence is often used when model parsimony is more relevant. Smaller values of the AIC and BIC indicate better model fit.

Having selected models on the basis of the information criteria, we provide an indication of the quantitative magnitude of effects by presenting average partial effects (APEs). Partial effects provide a quantitative interpretation of the results as they are measured in units of probability. For continuous regressors such as income, these are obtained by taking derivatives of the probabilities with respect to the variable in question. For discrete regressors such as lagged health status, they are obtained by taking differences. For the random effects specifications, the partial effects are averaged over the population distribution of heterogeneity and computed using the population averaged parameters (Wooldridge, 2002).

6. Results

6.1 Model selection

Separate models were estimated for each country and for both measures of limitations using the probit, logit and complementary log-log specifications. The information criteria for these models are presented in Tables 5 and 6. Both pooled and random effects specifications were used. The results, evaluated through the use of information criteria revealed a strong pattern across countries: in all cases the random effects probit model performs best (results are highlighted in bold). For the remainder of the paper we concentrate on results for this specification (full results are available on request).

Table 5: AIC and BIC for different specifications using HAMP1

		AIC	BIC
BE	PP	10455.87	10821.3
	REP	**9850.072**	**10223.45**
	PL	10476.86	10842.29
	REL	9919.272	10292.65
	CLL	10584.58	10950.02
	RE- CLL	10049.69	10423.06
DK	PP	11968.01	12326.02
	REP	**11427.56**	**11793.35**
	PL	11973.22	12331.23
	REL	11468.84	11834.63
	CLL	12000.78	12358.78
	RE-CLL	11541.9	11907.69
FR	PP	32149.59	32543.33
	REP	**30453.34**	**30855.84**
	PL	32167.1	32560.85
	REL	30542.21	30944.7
	CLL	32399.45	32793.2
	RE-CLL	30748.68	31151.17
GR	PP	26794.95	27195
	REP	**25695.07**	**26103.82**
	PL	26867.34	27267.4
	REL	25791.13	26199.89
	CLL	27039.04	27439.1
	RE-CLL	26068.35	26477.1
IR	PP	10673.7	11035.33
	REP	**10250.37**	**10619.86**
	PL	10707.27	11068.9
	REL	10298.39	10667.88
	CLL	10810.96	11172.59
	RE-CLL	10389.63	10759.11
IT	PP	28389.35	28806.85
	REP	**26651.19**	**27077.76**
	PL	28415.64	28833.14
	REL	26840.06	27266.64
	CLL	28627.47	29044.97
	RE-CLL	27203.43	27630.01
NL	PP	22680.13	23056.65
	REP	**21277.57**	**21662.47**
	PL	22660.35	23036.87
	REL	21372.41	21757.3
	CLL	22693.46	23069.98
	RE-CLL	21512.24	21897.13
PT	PP	34577.03	34982.77
	REP	**32993.54**	**33408.11**
	PL	34637.36	35043.11
	REL	33130.77	33545.34
	CLL	35008.78	35414.53
	RE-CLL	33577.9	33992.47
SP	PP	31568.61	31976.42
	REP	**30113.29**	**30529.97**
	PL	31717.33	32125.14
	REL	30248.08	30664.75
	CLL	32145.38	32553.19
	RE-CLL	30544.81	30961.48

*Note: PP stands for Pooled Probit;
REP, Random Effects Probit;
PL, Pooled Logit;
REL, Random Effects Logit;
CLL, Complementary Log-Log;
RE-CLL, Random Effects Complementary Log-Log model.

Table 6: AIC and BIC for different specifications using HAMP2

		AIC	BIC
BE	PP	4953.142	5309.284
	REP	**4704.454**	**5077.829**
	PL	4997.713	5353.855
	REL	4774.094	5147.469
	CLL	5057.596	5413.738
	RE-CLL	4812.65	5186.025
DK	PP	4687.181	5045.189
	REP	**4490.418**	**4856.209**
	PL	4713.917	5071.925
	REL	4532.675	4898.466
	CLL	4775.814	5133.822
	RE-CLL	4584.262	4950.053
FR	PP	19097.86	19491.61
	REP	**18056.68**	**18459.17**
	PL	19169.78	19563.53
	REL	18027.16	18429.65
	CLL	19365.58	19759.32
	RE-CLL	18301.62	18704.12
GR	PP	16340.49	16740.55
	REP	**15817.2**	**16225.95**
	PL	46398.67	16798.73
	REL	15887.68	16296.43
	CLL	16484.23	16884.29
	RE-CLL	15967.03	16375.78
IR	PP	3804.943	4166.565
	REP	**3646.722**	**4016.206**
	PL	3828.075	4189.697
	REL	3691.825	4061.309
	CLL	3862.306	4223.929
	RE-CLL	3732.451	4101.935
IT	PP	13535.59	13953.09
	REP	**12866.83**	**13293.4**
	PL	13699.45	14086.95
	REL	13035.87	13462.45
	CLL	13830.49	14247.99
	RE-CLL	13168.63	13595.21
NL	PP	11840.46	12216.99
	REP	**11275.21**	**11660.11**
	PL	11875.42	12251.95
	REL	11359.83	11744.72
	CLL	11966.05	12342.57
	RE-CLL	11443.34	11828.23
PT	PP	22178.32	22584.06
	REP	**21389.57**	**21804.14**
	PL	22293.86	22699.61
	REL	21519.27	21933.84
	CLL	22507.33	22913.08
	RE-CLL	21680.62	22095.19
SP	PP	16654.47	17062.28
	REP	**15970.46**	**16387.13**
	PL	16771.38	17179.19
	REL	16100	16516.67
	CLL	16909.93	17317.74
	RE-CLL	16220.62	16637.3

*Note: PP stands for Pooled Probit;
REP, Random Effects Probit;
PL, Pooled Logit;
REL, Random Effects Logit;
CLL, Complementary Log-Log;
RE-CLL, Random Effects Complementary Log-Log model.

6.2 Dynamic Random Effects Probits

Heterogeneity

The first source of persistence in health limitations to be considered is the time-invariant individual heterogeneity (μ_i). In the dynamic random effects probit model this is captured by the intra-class correlation coefficient (*rho*) which measures the proportion of the total unexplained variation that is attributed to the individual effect (σ^2). Table 7 shows the estimates of *rho* for HAMP1 and HAMP2 in each of the countries. For HAMP1 the values lie between .42 in Spain and .55 in the Netherlands, suggesting that heterogeneity accounts for between 42% and 55% of the unexplained variation in any limitation. For HAMP2 unobserved heterogeneity appears to be relatively less important with *rho* varying between .37 in Spain and .47 in France.

Table 7: *Intra-class correlation coefficients (rho) for random effects probit models*

Random effects Probit									
	HAMP1								
	BE	DK	FR	GR	IR	IT	NL	PT	SP
Rho	.531	.472	.501	.429	.429	.528	.548	.476	.420
	HAMP2								
	BE	DK	FR	GR	IR	IT	NL	PT	SP
Rho	.443	.445	.472	.385	.422	.438	.454	.415	.371

State dependence

The second source of persistence is state dependence (α). Table 8 presents the results, expressed as average partial effects (APE's), for the random effects probit specification. The estimate of state dependence in health limitations is statistically significant for all the countries considered and is large compared with the other partial effect estimates. For any limitations, the largest estimates are observed for Portugal (.164), Greece (.129), Denmark (.126) and Ireland (.121) while the smallest estimates are for Spain (.049), Italy (.081) and Belgium (.082). For severe limitations, the largest estimates correspond to Portugal (.113), Spain (.097) and France (.091), while Ireland (.024) and Belgium (.043) show the lowest values. With the exception of Spain, estimates of state dependence are lower for severe limitations than for any limitations.

Table 8: Average partial effects (APEs), random effects probit models

Random effects Probit									
	Any limitations								
	BE	DK	FR	GR	IR	IT	NL	PT	SP
Lagged Health	.082*	.126*	.097*	.129*	.121*	.081*	.097*	.164*	.049*
Primary	.002*	.018*	.032*	.033*	.019*	.018*	.010*	.065*	.030*
Secondary	.018*	.020*	.028*	.009	.010	.016*	.027*	.007	.027*
Lagged ln Income	.004	-.0005	-.006†	-.001	-.007	.002	-.010*	-.016*	-.007*
Lagged Self employed	-.013	.015	.005	-.003	-.015	.002	-.028*	.010	-.009
Lagged Unemployed	.015	.016	.018*	.027*	.048*	.005	.007	.032*	.025*
Lagged Retired	.004	.051*	.006	.032*	.016	.008	.001	.054*	.030*
Lagged Housework	.016	-.006	.033*	.018*	-.010	.002	.004	.041*	.031*
Lagged Inactivity	.087*	.062*	-.004	.091*	.161*	.039*	.018†	.066*	.076*
	Severe limitations								
	BE	DK	FR	GR	IR	IT	NL	PT	SP
Lagged Health	.043*	.058*	.091*	.081*	.024*	.068*	.067*	.113*	.097*
Primary	.002*	.006*	.013*	.012*	.005*	.008*	-.0001	.034*	.015*
Secondary	.010*	.007*	.012*	.008*	.005*	.005*	.006†	-.006	.006*
Lagged ln Income	.0002	-.004	-.002	-.004*	-.001	-.001	-.005*	-.008*	-.003*
Lagged Self employed	-.004	.004	.008	.001	-.002	.002	-.005	-.007†	-.001
Lagged Unemployed	.013*	.013*	.011*	.013*	.007†	.004*	.005	.024*	.007*
Lagged Retired	.007†	.019*	-.001	.029*	.004	.004*	-.008	.028*	.013*
Lagged Housework	.008†	-.002	.019*	.018*	.001	.003	.0001	.018*	.009*
Lagged Inactivity	.017*	.014*	.038*	.069*	.031*	.013*	.003	.048*	.031*

Note: Levels of statistical significance are reported at the 5% significance level (*) and 10% significance level (†).

Socioeconomic factors

The third source of persistence is observable socio-economic characteristics. The average partial effects for income, education and activity status are also presented in Table 8. It should be stressed that these are short-run impact effects computed from the dynamic specification. They capture the effect of a change in education (say) on the probability of reporting a limitation this year, having conditioned on the previous year's health state. Given the state dependence exhibited by HAMP1 and HAMP2, the cumulative long-run effects of these factors will be greater than the estimates provided here.

The estimated effects of educational achievement are positive for both definitions of health limitations and for almost all countries (Portugal is an exception for secondary education and severe limitations). The expected negative sign is found for household income, with the few exceptions, for example Belgium, not being statistically significant.

For activity status, compared to the baseline of being employed, the majority of the activity categories have a positive influence on reporting any or severe limitations. The exception is the self-employed, where the majority of effects are negative, suggesting a decreased probability of reporting any or severe limitations compared to employees. However, a number of these estimates are not statistically significant. Again, these estimates are derived conditional on initial period activity status and are identified through changes in status over the course of the panel survey. The greatest effect on reporting limitations is observed for inactivity status. These results are to be expected as labour market inactivity is likely to be highly correlated with claiming disability benefits. It has also been suggested that since ill-health may represent a legitimate reason for a person of working age to be outside the labour force, respondents who are not working may cite health problems as a way to rationalize behaviour. Further, for individuals for whom the financial rewards of continuing in the labour force are less there exists a financial incentive to report ill-health as a means of obtaining disability benefits, this is often cited as the 'disability route into retirement' (Riphahn, 1997; Blundell et al., 2002). For example, in a study of social security benefit programmes in The Netherlands, Kerkhofs and Lindeboom (1995) show that recipients of disability insurance systematically overstate their health problems.

Initial conditions

Our empirical model parameterizes the unobserved individual effect as a function of the initial period observations of the regressors and the dependent variable. Table 9 presents estimates of the lagged health and the initial period observation. The estimated coefficients on the initial period observations for health are all positive, implying there exists a positive correlation between the initial period observations and unobserved latent health. This is true for both any and severe limitations.

Table 9: Coefficients on lagged and initial values of health

	BE	DK	FR	GR	IR	IT	NL	PT	SP
Any limitations _ lagged	.652	.695	.559	.771	.768	.718	.561	.863	.338
Any limitations _ initial value	1.732	1.625	1.629	.750	1.232	1.077	1.620	.973	1.324
Severe limitations _ lagged	.665	.752	.822	.855	.867	1.022	.661	.946	.383
Severe limitations _ initial value	1.627	1.637	1.325	.621	1.069	1.034	1.662	.906	1.029

Note: All estimates are statistically significant at the 5% significance level.

Although not shown to conserve space, the coefficients on initial period observations for the other regressors are positive except for income. These imply a positive correlation between the set of variables and the unobserved individual effect. This is to be expected as one would expect that individuals entering the survey who are, for example, classified as inactive or retired would exhibit greater health limitations compared to the employed. While the coefficients on initial period income shows the expected negative sign, the coefficients are non-significant in the majority of countries.

7. Discussion

Health persistence is a well known phenomenon. What is less well known is the reasons for such persistence. In this paper we investigate the socio-economic drivers of health paying particular attention to the role of state dependence and unobserved heterogeneity. Conditioning on previous health status and specifying explanatory regressors lagged one period allows us to identify better the impact of socio-economic characteristics on health.

We use the full 8 waves available of the European Community Household Panel Users Database (ECHP-UDB). This is is a longitudinal dataset that allows us to explore the differences in the socioeconomic gradient in health and to perform comparative analysis between the different European countries included in the dataset. We focus on two indicators of health limitations (any limitation and severe limitation). Both pooled and random effects specifications for probit, logit and complementary log-log models are estimated. We include equivalised household income, education and activity status, together with other explanatory variables in our analysis. We use prior health status to control for the possibility of reverse causation or health selection and to quantify state dependence. We use a measure of income that precedes the health outcomes and we also control for initial health status to take account of selection effects.

After computing and comparing the information criteria for all the models considered, the dynamic random effects probit model is selected and average partial effects show the high level of persistence in both indicators of health limitations. We decompose observed persistence into components due to unobserved heterogeneity and state dependence and find that both play important roles in the determination of health limitations.

In general, while the two measures do not correlate perfectly, we observe some consistency in the rankings of unobserved heterogeneity across countries for our two measures of health limitations (HAMP1 and HAMP2). Countries with relatively high estimates of unobserved heterogeneity for severe limitations tend to have relatively high estimates for any health limitations and vice versa. However, the same level of consistency is not observed for the estimates of state dependence as evidenced through average partial effects. So while Portugal exhibits the highest level of state dependence for both any and severe health limitations, Spain shows the lowest level of state dependence for any limitations, but the second highest for severe limitations and Ireland shows the lowest level of state dependence for severe limitations, but the fourth highest for any limitations. Further while the exact relationship between state dependence and the degree of unobserved heterogeneity is unclear, comparing results across countries indicates that relatively high levels of state dependence are generally associated with relatively low levels of unobserved heterogeneity and vice versa. This may indicate cultural differences in the reporting of health which may differ systematically across countries or differences in the nature of health problems that are reflected in the components of health that can be thought of as those due to state dependence and those due to unobservable characteristics. The former may include factors such as the cumulative effect of a history of health problems or the effectiveness and availability of health care, while the latter may reflect socio-economic characteristics not fully captured by the included regressors, or unobserved characteristics such as lifestyle choices, time preference and aversion to risk.

There is heterogeneity in the magnitude of the quantitative effect of SES in health limitations across the nine European countries considered, although the direction of the contribution is similar for all of them. In general, the health returns to SES show reasonable consistency in effects across the two health measures such that, for example, countries exhibiting a high income gradient for any limitations also exhibit a high income gradient against severe limitations (e.g. Portugal, the Netherlands). This is also true for returns for education. In general, across all estimates higher levels of income and education decrease the probability of reporting limitations in daily activities. The effect of activity status is larger than the effect of income and education. Inactivity is associated with the largest absolute effect and will reflect, in part, individuals claiming disability allowances due to ill health. The results indicate that health problems should be regarded as a dynamic phenomenon.

References

Adams, P., Hurd, M.D., McFadden, D., Merril, A., Ribeiro, T. 2003. Healthy, wealthy, and wise. Tests for direct causal paths between health and socioeconomic status. *Journal of Econometrics* 112, 3-56.

Arendt, J.N., 2005. Does education cause better health? A panel data analysis using school reforms for identification. *Economics of Education Review* 24, 149-160.

Benzeval, M., Judge, K., 2001. Income and health: the time dimension. *Social Science & Medicine* 52, 1371-1390.

Benzeval, M., Taylor, J., Judge, K., 2000. Evidence on the relationship between low income and poor health: is the government doing enough?. *Fiscal Studies* 21, 375-399.

Blundell, R., Meghir, C., Smith, S., 2002. Pension incentives and the pattern of early retirement. *Economic Journal* 112, 153-170.

Bound, J., 1991. Self-reported versus objective measures of health in retirement models. *Journal of Human Resources* 26, 106-138.

Buckley, N.J., Denton, F.T., Robb, L., Spencer, B.G. 2004. The transition from good to poor health: an econometric study of the older population. *Journal of Health Economics* 23, 1013-1034.

Butler, J.S., Moffit, R., 1982. A computationally efficient quadrature procedure for the one-factor multinomial probit model, *Econometrica* 50, 761-764.

Chamberlain, G., 1980. Analysis of covariance with qualitative data. *Review of Economic Studies* 47, 225-238.

Chay, K.Y., Hyslop, D.R., 2000. Identification and estimation of dynamic binary response panel data models: empirical evidence using alternative approaches. *University of California at Berkeley Working Paper*

Contoyannis, P., Rice, N., 2001. The impact of health on wages: Evidence from the British Household Panel Survey. *Empirical Economics* 26, 599-622.

Contoyannis, P., Jones, A.M., Rice, N., 2004a. The dynamics of health in the British Household Panel survey. *Journal of Applied Econometrics* 19, 473-503.

Contoyannis, P., Jones, A.M., Rice, N., 2004b. Simulation-based inference in dynamic panel probit models: an application to health. *Empirical Economics* 29, 49-77.

Deaton, A.S., 2003. Health, inequality, and economic development. *Journal of Economic Literature* XLI, 113-158.

Deaton, A.S., Paxson, C.H., 1998. Aging and inequality in income and health. *The American Economic Review* 88, 248-253.

Disney, R., Emmerson, C., Wakefield. M., 2006. Ill-health and retirement in Britain: a panel data-based analysis. *Journal of Health Economics* 25, 621-649.

Ettner, S.L., 1996. New evidence on the relationship between income and health. *Journal of Health Economics* 15, 67-85.

Fritjers, P., Haisken-DeNew, J.P., Shields, M.A., 2005. The causal effect of income on health: evidence from German reunification. *Journal of Health Economics* 24, 997-1017.

Grossman, M., 2000. The human capital model. In Culyer, A.J. Newhouse, J.P. (eds.), *Handbook of Health Economics*, Elsevier, Amsterdam, pp. 347-408.

Hagan, R., Jones, A.M., Rice, N., 2006. Health and retirement in Europe. HEDG working paper #06/09, University of York.

Halliday, T.J., 2005. Heterogeneity, State Dependence and Health. Working Paper No. 05-03, Department of Economics, University of Hawaii at Manoa.

Hauck, K., Rice, N., 2004. A longitudinal analysis of mental health mobility in Britain. *Health Economics* 13, 981-1001.

Heckman, J., 1981. The incidental parameters problem and the problem of initial conditions in estimating a discrete time-discrete data stochastic process. In Manski, D.F., McFadden, D. (Eds), *Structural analysis of discrete data with econometric applications*, MIT Press, Cambridge MA, pp. 179-195.

Hernández-Quevedo, C., Jones, A.M., López-Nicolás, Á., Rice, N., 2006. Socioeconomic inequalities in health: a comparative longitudinal analysis using the Ecuropean Community Household Panel. *Social Science & Medicine* 63, 1246-1261.

Hernández-Quevedo, C., Jones, A.M., Rice, N., 2007. Reporting bias and heterogeneity in self-assessed health. Evidence from the British Household Panel Survey. *Cuardernos de ICE*, forthcoming.

Hurd, M., Kapteyn, A., 2003. Health, wealth, and the role of institutions. *Journal of Human Resources* 38, 386-415.

Jensen, R.T., Richter, K., 2003. The health implications of social security failure: evidence from the Russian pension crisis. *Journal of Health Economics* 88: 209-236.

Jones, A.M., Koolman, X., Rice, N., 2006. Health-related non-response in the British Household Panel Survey and European Community Household Panel: using inverse-probability-weighted estimators in non-linear models. *Journal of the Royal Statistical Society, Series A* 169, 543-569.

Kerkhofs, M., Lindeboom, M., 1995 Subjective health measures and state dependent reporting errors. *Health Economics* 4, 221-235.

Kerkhofs, M., Lindeboom, M., 1997. Age related health dynamics and changes in labour market status. *Health Economics* 6, 407-423.

Kunst, A.E., Geurts, J.J., van den Berg, J., 1995. International variation in socioeconomic inequalities in self reported health. *Journal of Epidemiology and Community Health* 49, 117-123.

Lindahl, M., 2005. Estimating the effect of income on health and mortality using lottery prizes as an exogenous source of variation in income. *Journal of Human Resources* 40, 144-168.

Meer, J., Millar, D.L., Rosen, H.S., 2003. Exploring the health-wealth nexus. *Journal of Health Economics* 22, 713-730.

Mundlak, Y., 1978. On the pooling of time series and cross section data. *Econometrica* 46, 69-85.

Peracchi, F., 2002. The European Community Hosehold Panel: A Review, *Empirical Economics* 27, 63-90.

Rice, N., Roberts, J., Jones, A.M., 2006 Sick of work or too sick to work? Evidence on health shocks and early retirement from the BHPS. *HEDG Working Paper*, #06/13, University of York.

Riphahn, R.T., 1997. Disability, retirement and unemployment: substitute pathways for labour force exit? An empirical test for the case of Germany. *Applied Economics* 29, 551-561.

Salas, C., 2002. On the empirical association between poor health and low socioeconomic status at old age. *Health Economics* 11, 207-220.

Smith, J.P., 1999. Healthy bodies and thick wallets. *Journal of Economic Perspectives* 13, 145-166.

Smith, J.P., 2004. Unravelling the SES health connection. *Working Paper 04-02 The Institute for Fiscal Studies*, London.

Smith, J.P., 2005. The Impact of SES on health over the life-course. *RAND Working Paper.*

Terza, J.V., 1985. Ordinal probit: A generalization. *Communications on Statistics – Theory and Methods* 14, 1-11.

Van Doorslaer, E.K.A., Jones, A.M., 2004. Income-related inequalities in health and health care and the ageing European population. *Health Economics* 13, 605-608.

Van Doorslaer, E.K.A., Koolman, X., 2004. Explaining the Differences in Income-Related Health Inequalities across European Countries. *Health Economics*, 13, 609-628.

Van Doorslaer, E.K.A., Koolman, X., Jones, A.M., 2004. Explaining income-related inequalities in doctor utilisation in Europe. *Health Economics*, 13, 629-647.

Van Ourti, T., 2003. Socioeconomic inequality in ill-health amongst the elderly. Should one use current or permanent income?. *Journal of Health Economics* 22, 219-241.

Wooldridge, J.M., 2002. *Econometric analysis of cross-section and panel data.* MIT Press, Cambridge MA.

Wooldridge, J.M., 2005. Simple solutions to the initial conditions problem in dynamic, nonlinear panel data models with unobserved heterogeneity. *Journal of Applied Econometrics* 20, 39-54.