The causal effect of socioeconomic characteristics in health limitations across Europe: a longitudinal analysis using the European Community Household Panel (ECHP) dataset.

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1. Introduction

This paper uses the *European Community Household Panel Users' Database* (ECHP-UDB) to analyse the dynamics of the socioeconomic (SE) gradient in two binary indicators of health limitations across European Union Member States. The ECHP-UDB is a standardised annual longitudinal survey, which provides 8 waves (1994-2001) of comparable micro-data about living conditions in the European Union Member States (EU-15). Our analysis focus 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?", included in the ECHP-UDB.

The main aim is to investigate the causal effect of the SE characteristics in health limitations within and between the Member States of the European Union. For that purpose, we exploite the longitudinal nature of the ECHP-UDB. We are interested in whether, and to what extent, SE variables as education, income and job status affect health limitations and how this varies across time and countries included in the ECHP-UDB, considering the individuals by groups of age and sex.

The ECHP is a longitudinal dataset that allows the researcher to explore the differences in the socioeconomic gradient in health across countries and to perform comparative analysis between the different European countries included in the dataset. The panel nature of the dataset allows us to run both pooled and random effects probit models. Taking into account the longitudinal perspective of the data, we are provided with additional information on the dynamics of individual health limitations and income. A long-run perspective gives us useful information for public health policies, if policymakers are interested in the lifetime history of the individual.

Little attention has been devoted to health dynamics in the past. We are interested in studying the causal effect of SE factors in two indicators of health limitations from a dynamic perspective, which provides us with richer information about this relationship than a cross-sectional analysis. Even though policies have been applied to reduce the level of inequalities in health, there is evidence that overall inequalities persist over time (Contoyannis, Jones and Rice, 2004) and a dynamic approach should be taken into account.

The focal points of the dynamic analysis as reported by Contoyannis, Jones and Rice (2004) are the following: contributions of state dependence, heterogeneity and serial correlation, issues that we will be analysing in this study.

Finally, attention will be devoted to study the existence of health-related attrition and its consequences. Failing to account for attrition leads to misleading estimates of health dynamics and the relationship between health and SE status (Contoyannis, Jones and Rice, 2004).

2. Literature Review

There are several studies that investigate the causal effect of SE characteristics on health. However, it has been argued that this gradient is not well understood (Ettner, 1996; Deaton & Paxon, 1998; Benzeval et al, 2000) mainly due to two issues: 1. the use of occupational class as a proxy for income, which creates some confusion, 2. the possibility of reverse causality, i.e. that poor health can lead to low income as well as vice versa (Benzeval et al, 2000).

The study of the association between health and SE status is an issue of relevance for public health, as policy indications can be derived to reduce health inequalities and improve health in each society (Ettner, 1996; Fritjers et al., 2003).

The previous literature on this association is limited, because most of the studies focus on cross-sectional data, as reported by Fritjers et al (2003) and Benzeval & Judge (2001). In fact, panel data provides further information on dynamics of individual health and income and its impact on inequalities on these periods. Besides, it allows to take into account the lifetime history of the individual, which could provide useful information for policymakers interested in that approach. However, cross-sectional surveys do not allow neither to give much evidence on causal effects (Fritjers et al., 2003) nor in the direction of the causation (Benzeval & Judge, 2001).

Several limitations have been mentioned in the literature related to the type of study we want to pursue:

1. Presence of endogeneity, that is, the existence of unobservable individual characteristics, which jointly determine both income and health, as for example, the social background of the individual.
2. Reverse causality which implies that the direction of the causation could be happening from health to SE status or vice versa.
3. Identification of the most suitable measures of income and health that should be used in the analysis, which is usually an issue related to data constraints for some surveys.

Health dynamics has been recently studied by Contoyannis, Jones and Rice (2004), work that we use as our benchmark for our analysis.

Contoyannis, Jones and Rice (2004) base their study on the British Household Panel Survey (BHPS), focusing on three issues. Firstly, they check 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 consequences. Finally, they explore the relationship between SE characteristics (education and income) and a measure of self-reported health (SAH) included in the BHPS.

Contoyannis, Jones and Rice (2004) model SAH by using dynamic Pooled Ordered Probit models and specifying the functional form of a latent variable representing "true health". They deal with correlated individual effects and the initial conditions problem by focusing on Wooldridge's (2005) approach, while they perform a variable-addition test for attrition bias (Verbeek & Nijman, 1992) and apply inverse probability weighting (IPW) to adjust for attrition when they estimate pooled models.

For the purpose of their study, they compare the estimates obtained when using a balanced panel (BP) and an unbalanced panel (UP). Besides, all available data is used to evaluate the impact of attrition. To analyse non-response and attrition bias, they compare the number of observations across waves together with the bivariate relationship between attrition rates and SE characteristics.

They found evidence of attrition related to health in the data, but estimates of state dependence and of the SE gradient in health has not been distorted by this bias. Heterogeneity was found to account for around 30% and positive state dependence was shown in the results of the models.

A more detailed study on attrition bias has been presented by Jones, Koolman and Rice (2006).

Jones, Koolman and Rice (2006) analyse health-related non-response using a categorical variable of SAH, as it may have consequences in dynamic models. They use a BP and UP and correct for non-response using inverse probability weighting (IPW) (Wooldridge, 2002).

The objective of Jones, Koolman and Rice (2006) is to find evidence of health-related non-response in panel data and the consequences it has for modelling the relationship between SE status and SAH. For that purpose, they describe the pattern of non-response due to health that is revealed by the BHPS and the ECHP dataset.

They use 9 waves available of the BHPS and they concentrate in SAH, self-reported functional limitations, specified health problems and an indicator of being registered as a disable person. From the ECHP, they use and indicator of any limitation and severe limitation.

They found evidence of non-response related to health in both datasets, but with a limited impact on the estimates of health dynamics and estimates of the relationship between SE characteristics and SAH.

Evidence on income-related inequalities in health problems for the 8 periods covered by the ECHP (1994 – 2001) have been already provided at the EU-15 level (HJLR, 2005). In particular, income-related inequalities in health limitations have been found in the 14 member states considered, in both the short and the long run. These inequalities favour the richest individuals in each society and they show an increasing pattern in most of the countries. This evidence justifies measures of public policies to reduce these inequalities in the EU[1]. Besides, this study suggests the use of a longitudinal perspective when measuring and interpreting inequalities in health, against the approach usually found in the literature that focus on cross-sectional data.

However, this study presents some limitations, as only health inequalities due to differences in income levels are studied, without taking into account other socioeconomic factors as education and job status. HJLR (2005) consider, inequality as an overall measure, without taking into account other SE characteristics of the individuals when measuring inequalities in health problems. We are interested in quantifying the causal effect of SE characteristics in health problems.

3. The ECHP-UDB data

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 8 waves (1994 - 2001) of comparable micro-data about living conditions in the 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 and 130,000 adults were interviewed at each wave. 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.

[1] Action to reduce health inequalities in EU aims: 1. To improve everyone's level of health closer to that of the most advantaged; 2. To ensure that the health needs of the most disadvantaged are fully addressed; 3. to help the health of people in countries and regions with lower levels of health to improve faster. *European Commission*.

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, Luxembourg and the United Kingdom. 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, together with comparable versions of the British Household Panel Survey (BHPS), the German Socioeconomic Panel (GSOEP) and the Panel Survey for Luxembourg (PSELL)[3].

In this preliminary version of the paper, results have been provided only for Spain, for the 8 waves of data available. However, the study will be generalised to most of the Member States of the EU that are contained in the ECHP, for the full number of available waves. These are: Austria (waves 2 – 8), Belgium (1 – 8), Denmark (1 – 8), Finland (3 – 8), France (1 – 8), Germany (1 – 3), Greece (1 – 8), Ireland (1 – 8), Italy (1 – 8), Luxembourg (1 – 3), The Netherlands (1 – 8), Portugal (1 – 8), and United Kingdom (1 – 3), although Germany, Luxembourg and UK may be dropped when performing the dynamic estimation.

Sample and variables

Balanced Panel

We need a full set of waves for each individual and we use a balanced sample of respondents, which implies that only individuals from the first wave who were interviewed in each subsequent wave are included in the analysis[4]. 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. Exceptions are Spain and Italy with both having notably larger samples and Luxembourg and the United Kingdom with notably smaller samples.

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[2] Note however that the data for Sweden is not longitudinal, and has been derived from repeated cross-sections. We do not use data for Sweden.

[3] Data for Germany, Luxembourg and United Kingdom are taken from the original ECHP survey.

[4] 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 (2005) have provided 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.

[Insert Table 1 around here]

Health limitations

The ECHP-UDB dataset contains some limited information on health outcomes and health care utilisation. We use the information on health limitations, in particular responses provided to the question[5]: "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[6]. We focus on two binary measures of health problems 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 any limitations (severe or to some extent) versus no limitations; the second dummy (HAMP2) represents an indicator of severe limitations versus no limitations or limited to some extent.

Explanatory variables

Five variables represent marital status (*Widowed*, *Single*, *Divorced*, *Separated*) with *Married* as the reference category. Three dummy variables have been constructed to represent maximum level of education attained: *Tertiary* (Third level), *Secondary* (second stage of secondary level) and *Primary* (less than second stage of secondary education), with *Tertiary* being the base case for the education variables. 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 and the Consumer Price Index. It is equivalised by the OECD-modified scale to adjust for household size and composition.

[5] The question is coded PH003A in the ECHP-UDB.

[6] 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?".

There are six possible categories for job status: *Self-employed*, *Unemployed*, *Retired*, *Housework* and *Inactive*, with *Employed* individuals being the reference case. 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. See Table 2 for a full list of variables used in this study.

[Insert Table 2 around here]

Descriptive Analysis using a Balanced Panel

Descriptive analysis of HAMP, HAMP1 and HAMP2

Figure 1 shows the distribution of HAMP for all countries and it shows that health limitations present a similar distribution across countries, with most individuals reporting not perceiving any or severe limitations in their daily activity.

[Insert Figure 1 around here]

Figures 2 and 3 show the distribution of HAMP1 and HAMP2 respectively, for each country. For the variable HAMP1, the country with the highest percentage of individuals who report any limitation is Finland at 28.2%, followed by Portugal (25.6%) and the UK (25.2%). The country with the lowest percentage is Italy (12.6%), followed by Belgium (14.8%) and Ireland (16.2%). Similar results are found for the variable HAMP2. Portugal has the highest percentage of individuals who report being severely hampered (10.3%), followed by France (9.5%) and Finland (7.6%), while Ireland, Italy and Belgium have the lowest percentages at 3.4%, 4.3% and 4.6%, respectively.

[Insert Figure 2 around here]

[Insert Figure 3 around here]

Descriptive analysis by level of income

Table 3 shows the percentage of individuals who report either any or severe limitations across income quintiles. 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 26% in the first income quintile in the UK. The range for severe health limitations goes from 1.4% in the fifth quintile for Ireland to 15.4% in the second income quintile in Portugal.

Country-specific results show a clear association between income and health. In general, there exists a gradient across income quintiles in the reporting of both severe and any health limitations, 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. Similarly there is variation across income quintiles in the proportion of respondents reporting health limitations to some extent. For Luxembourg, the proportion ranges from 20.7% in the lowest quintile to 11.5% in the highest. This is in contrast to Italy where the corresponding figures are much lower at 9.2% and 6.3%, respectively.

[Insert Table 3 around here]

4. Methods

The general latent variable specification for a binary choice model in a dynamic context is given by expression (1):

$$h_{it}^{*} = x_{it}^{'}\beta + \gamma h_{it-1} + \eta_i + \varepsilon_{it} \qquad (1)$$

Where x_{it} is the set of explanatory variables, η_i is a time-invariant individual effect and ε_{it} is a time and individual-specific error term.

Hence,

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

If we assume that the distribution of ε_{it} is symmetric with distribution function F(.),

$$P(h_{it} = 1 | x_{it}, \beta, \gamma, h_{it-1}, \eta_i) = P(\varepsilon_{it} > -x'_{it}\beta - \gamma h_{it-1} - \eta_i) = F(x'_{it}\beta + \gamma h_{it-1} + \eta_i) \tag{3}$$

In our study, we assume a standard normal distribution, that is, a probit model. Hence,

$$\Pr[h_{it} = 1 | x_{it}, \beta, \gamma, h_{it-1}, \eta_i] = \Phi(x'_{it}\beta + \gamma h_{it-1} + \eta_i)\ , \tag{4}$$

where Φ(.) is the standard normal cumulative density function (cdf).
If conditional independence is assumed, the joint density for the i[th] observation h_i = (h_{i1}, …, h_{iT}) is:

$$f(h_i | x_i, \beta, \gamma, h_{it-1}, \eta_i,) = \prod_{t=1}^{T} F(\eta_i + x'_{it}\beta + \gamma h_{it-1})^{h_{it}} (1 - F(\eta_i + x'_{it}\beta + \gamma h_{it-1}))^{1-h_{it}} \tag{5}$$

Several models can be used to model health limitations using panel data. In this paper, three main estimation procedures are taken into account: pooled probit model, random effects probit model and complementary log-log model.

4.1. Pooled Probit Model

The Pooled Probit (PP) model does not take into account that the panel dataset contains repeated observations, that is, it pools all the observations together, without considering that individuals are measured repeatedly, from wave 1 to wave 8, if they have not dropped from the panel within the 8 waves.

The estimates resulting from the PP model are consistent, although it does not take into account the structure of the error term and hence, the model is estimated using a mispecified likelihood function.

4.2. Random Effects Probit Model

The random effects probit (REP) model assumes that both components of the error term (η_i, ε_{it}) are normally distributed and that both are independent of the x's, which is a strong assumption. Different approaches have been shown in the literature dealing with relaxing this assumption.

Chamberlain (1984) presents a correlated random effects model to deal with individual RE that are correlated with the explanatory variables. This approach consists in specifying this relationship as a linear regression of the value of the explanatory variables in all the waves of the panel. If there is sufficient within-individual variation, it is possible to obtain separate estimates of the β's and to disentangle the correlation between the x's and the time-invariant individual-specific effect η_i.

Chamberlain's model specifies:

$$\eta_i = x'_{1i}\pi_1 + \ldots + x'_{Ti}\pi_T + \xi_i \, , \qquad (6)$$

where $\xi_i | x_i \sim N(0, \sigma_\eta^2)$

An alternative approach has been suggested by Mundlak (1978), which specifies this relationship as a linear regression of the mean value of the explanatory variables, that are averaged over t for a given i:

$$\eta_i = \bar{x}'_i \pi + \xi_i \qquad (7)$$

The vector π will equal 0 if the explanatory variables are uncorrelated with the effects.

Wooldridge (2005) provides an approach to deal with correlated individual effects and the initial conditions problem in dynamic, nonlinear unobserved effects probit model. It consists in finding the distribution conditional on the initial value.
There are two factors that can be problematic: 1. the starting point of a survey is not the beginning of a process, 2. individuals inherit different unobserved and time-invariant characteristics which affect outcomes in every period, issue that can lead to endogeneity bias in dynamic models with covariance structures that are not diagonal (Contoyannis et al., 2004).
The approach provided by Wooldridge (2005) models the distribution of the unobserved effect conditional on the initial value and any strictly exogenous explanatory variables. The resulting likelihood function is based on the joint distribution of the observations conditional on the initial observations (Conditional maximum likelihood – CML).

4.3. Complementary log-log binary choice model

Complementary log-log models are frequently used when the probability of an event is very small or very large. Unlike logit and probit the complementary log-log function is asymmetrical.

The log-likelihood function for complementary log-log is:

$$\ln L = \sum w_j \ln F(x_j b) + \sum w_j \ln\left(1 - F\left(x_j b\right)\right)$$

where F(z) = 1-exp(-exp(z)) and w_j denotes optional weights.

5. Estimation strategy

We explore the relationship between health and SE status, in particular, the relationship between reporting health limitations in the daily activity and household income, education and job status, among other SE controls as marital status, household size, number of children in the household with a certain age and age groups by gender.

Non-linear panel data models (probit) are estimated. There are several methodological challenges in this approach, as reported by Contoyannis, Jones and Rice (2004) the possibility of correlated individuals effects, the initial conditions problem and attrition bias.

We use dynamic panel probit specifications on a balanced sample to model HAMP1 & HAMP2. Previous report on health limitations is included in our specification to capture state dependence and reduce bias due to reverse causality (see Adams et al, 2003). Hence, this model can be seen as a first-order Markov process. These models can be regarded as reduced form specification, that is, variables such as medical care and lifestyle are not included (Contoyannis et al, 2004).

Our model presents the following specification for its binary latent variable:

$$h_{it}^{*} = x_{it}'\beta + \gamma h_{it-1} + \delta h_{io} + u_{it} \qquad (8)$$

Where u_{it} is a two-component error term, made of a time-invariant individual effect (η_i) plus a time and individual-specific error term (ε_{it}), where ε_{it} follows a Normal (0, 1) and is independent of the x's and η_i. Hence,

$$u_{it} = \eta_i + \varepsilon_{it} \qquad (9)$$

We apply Wooldridge (2005) approach to deal with the initial conditions problem by including the initial value of health limitations h_{io}.

To allow for the possibility that the observed regressors may be correlated with the individual effect we parameterize the individual effect (Mundlak, 1978; Chamberlain, 1984; Wooldridge, 2005).

We implement Wooldridge (2005) approach by parameterizing the distribution of the individual effects, by including both initial values and lagged values of some of the regressors.

6. Results

Marginal effects are shown for Pooled Probit Model and Complementary log-log, hence, estimates are comparable. Results are shown in Table 4 for both Hamp1 and Hamp2.

To choose which model best fits our data, we use two model selection criteria:

1. Akaike information criterion:

$$AIC(K) = s_y^2(1-R^2)e^{2K/n}$$

2. Schwartz or Bayesian information criterion:

$$BIC(K) = s_y^2(1-R^2)n^{K/n}$$

Besides, we use the Reset test to check whether our models are misspecified.

Results are shown in Table 5 for pooled probit model, random effects probit and complementary log-log models.

Results in Table 5 suggest that the Random Effects model is the best model for both Hamp1 and Hamp2 in all the countries considered in our analysis.

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

Wave	D	DK	NL	B	L	F	UK	Irl	I	EL	E	P	A	Fin
1	8,036	2,536	4,656	3,008	1,779	7,226	5,382	2,748	9,539	6,384	7,549	7,348	-	-
2	8,036	2,536	4,656	3,008	1,779	7,226	5,382	2,748	9,539	6,384	7,549	7,348	4,001	-
3	8,036	2,536	4,656	3,008	1,779	7,226	5,382	2,748	9,539	6,384	7,549	7,348	4,001	3,893
4	-	2,536	4,656	3,008	-	7,226	-	2,748	9,539	6,384	7,549	7,348	4,001	3,893
5	-	2,536	4,656	3,008	-	7,226	-	2,748	9,539	6,384	7,549	7,348	4,001	3,893
6	-	2,536	4,656	3,008	-	7,226	-	2,748	9,539	6,384	7,549	7,348	4,001	3,893
7	-	2,536	4,656	3,008	-	7,226	-	2,748	9,539	6,384	7,549	7,348	4,001	3,893
8	-	2,536	4,656	3,008	-	7,226	-	2,748	9,539	6,384	7,549	7,348	4,001	3,893
Men	11,640	9,776	16,928	10,808	2,571	26,936	7,119	10,512	36,840	23,224	27,712	26,960	13,370	11,484
Women	12,468	10,512	20,320	13,256	2,766	30,872	9,027	11,472	39,472	27,848	32,680	31,824	14,637	11,874
Total	24,108	20,288	37,248	24,064	5,337	57,808	16,146	21,984	76,312	51,072	60,392	58,784	28,007	23,358

Table 2: Explained and explanatory variables

HAMP	Hampered in daily activities by any physical or mental health problem, illness or disability:
	1 if severely hampered by any health problem
	2 if some extend hampered by any health problem
	3 if not hampered by any health problem
HAMP1	1 if severely hampered or to some extend by any health problem, 0 otherwise
HAMP2	1 if severely hampered by any health problem, 0 otherwise
SEPARATED	1 if separated, 0 otherwise
DIVORCED	1 if divorced, 0 otherwise
WIDOWED	1 if widowed, 0 otherwise
NVRMAR	1 if never married, 0 otherwise
SECONDARY	1 if second stage of secondary level, 0 otherwise
PRIMARY	1 if less than second stage of secondary level, 0 otherwise
HH_SIZE	Number of people in household including respondent
NCH04	Number of children in household aged 0 - 4
NCH511	Number of children in household aged 5 - 11
NCH1218	Number of children in household aged 12 - 18
INCOME	Equivalised total net household income (PPP & CPI)
AGE2635M	Men with age between 26 and 35
AGE3645M	Men with age between 36 and 45
AGE4655M	Men with age between 46 and 55
AGE5665M	Men with age between 56 and 65
AGE6675M	Men with age between 66 and 75
AGE7685M	Men with age between 76 and 85
AGE86M	Men with 86 years old or more
AGE1625F	Women with age between 16 and 25
AGE2635F	Women with age between 26 and 35
AGE3645F	Women with age between 36 and 45
AGE4655F	Women with age between 46 and 55
AGE5665F	Women with age between 56 and 65
AGE6675F	Women with age between 66 and 75
AGE7685F	Women with age between 76 and 85
AGE86F	Women with 86 years old or more
SELFEMPLOY	1 if self-employed, 0 otherwise
UNEMPLOYED	1 if unemployed, 0 otherwise
RETIRED	1 if retired, 0 otherwise
HOUSEWORK	1 if doing housework, looking after children or other persons, 0 otherwise
INACTIVE	1 if other economically inactive, 0 otherwise

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
Germany	17.72	17.15	15.67	14.33	14.90	9.63	7.34	5.72	5.53	4.72
Denmark	20.38	17.54	16.64	13.81	11.23	10.75	7.12	3.43	2.67	2.08
Netherlands	18.61	17.36	15.53	14.86	13.66	10.25	9.08	6.73	5.55	5.09
Belgium	14.46	10.70	8.94	8.79	8.71	9.53	5.57	3.17	2.18	2.55
Luxembourg	20.65	18.36	18.91	12.91	11.53	7.14	5.16	4.58	4.16	2.34
France	16.69	15.01	12.98	10.18	10.18	14.11	11.90	10.52	5.65	5.65
UK	25.76	21.77	17.10	13.66	14.54	9.76	10.48	7.06	4.22	2.13
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
Greece	14.39	11.81	9.73	9.50	6.43	12.26	9.44	7.55	6.51	3.49
Spain	14.71	15.51	13.44	10.49	7.01	7.23	7.36	7.08	5.38	2.59
Portugal	19.35	18.53	15.93	14.25	11.14	14.30	15.36	11.34	8.43	5.50
Austria	18.30	14.44	12.23	11.40	11.25	8.18	5.33	4.97	3.90	3.32
Finland	22.21	22.09	19.87	20.46	18.63	10.09	9.78	6.80	6.38	5.61

Note: Both the highest and lowest percentages of responses by income quintiles across countries have been highlighted in this table

Figure 1: **Distribution of health limitations (HAMP) for each country**

Figure 2: **Percentage of individuals hampered (HAMP1), across the Member States**

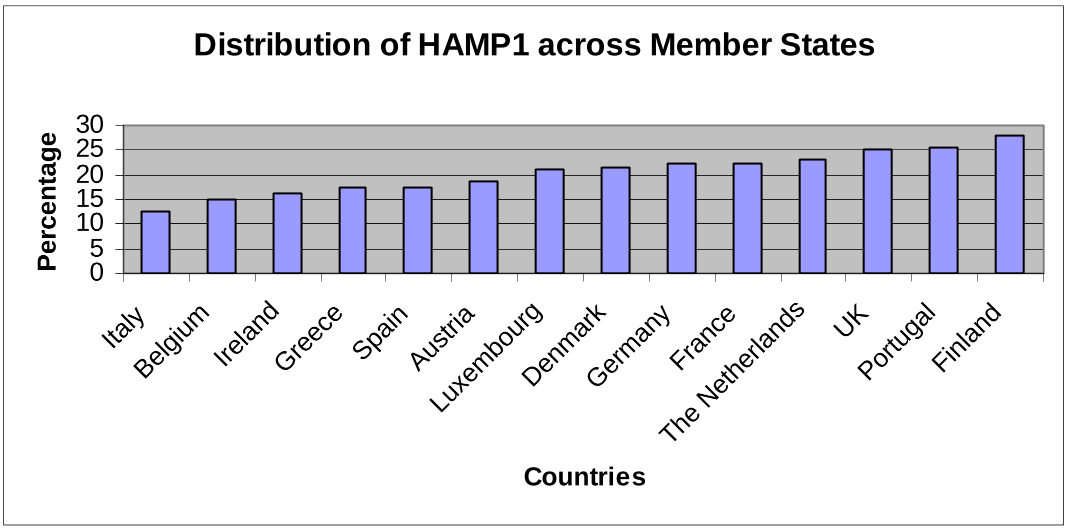

Figure 3: Percentage of individuals severely hampered (HAMP2) across the Member States

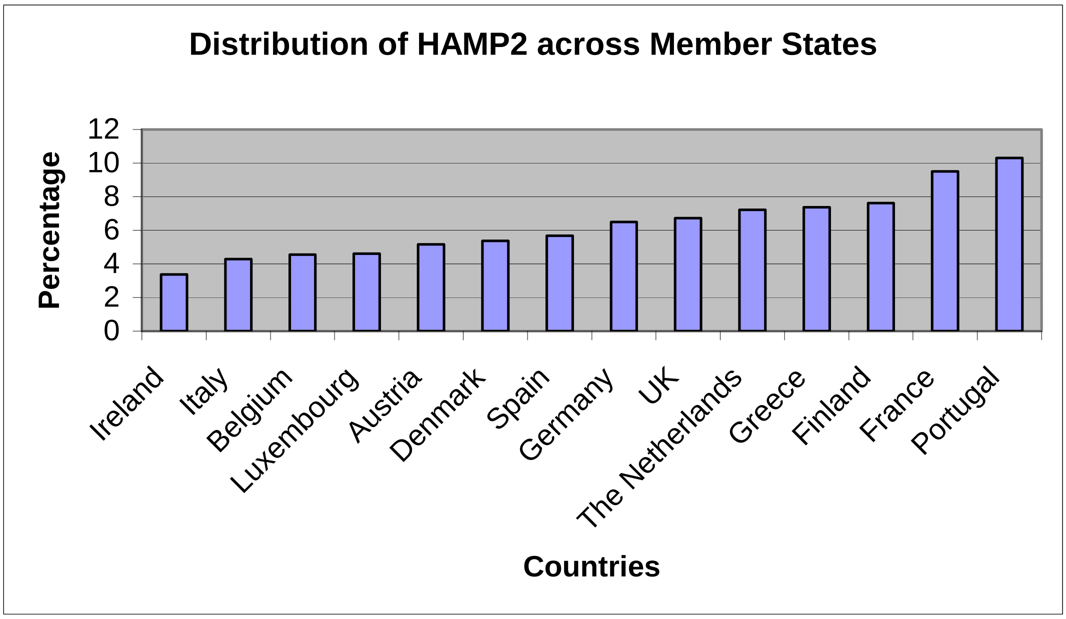

Table 4. Pooled Probit and Complementary log-log, marginal effects

	DK				NL				B			
	PPM		CLL		PPM		CLL		PPM		CLL	
	ME_H1	ME_H2	ME_H1	ME _ H2	ME_H1	ME_H2	ME_H1	ME_H2	ME_H1	ME_H2	ME_H1	ME_H2
hamp1/2_lag	0.466	.276	.420	.157	.471	.334	.426	.263	.399	.227	.328	.137
primary	-0.03	-.011	-.020	-.005	-.050	-.014	-.031	-.009	-.026	-.011	-.016	-.008
secondary	-0.008	-.003	-.006	-.001	-.025	-.003	-.014	-.001	-.009	.001	-.004	.0001
ln_inc_lag	-0.004	-.004	.007	-.001	-.015	-.007	-.011	-.004	.004	.0001	.004	.001
selfemploy_lag	0.0001	.005	.002	.008	-.031	-.007	-.029	-.007	-.007	-.001	-.004	.004
unemployed_lag	0.046	.029	.028	.028	.033	.018	.025	.015	.036	.025	.024	.028
retired_lag	0.1	.046	.081	.039	.014	-.004	.009	.001	.022	.015	.016	.018
housework_lag	-0.02	-.004	-.009	.003	.016	.005	.013	.006	.035	.017	.024	.022
inactive_lag	0.131	.043	.104	.041	.044	.014	.029	.012	.183	.043	.082	.036

	F				Irl				I			
	PPM		CLL		PPM		CLL		PPM		CLL	
	ME_H1	ME_H2	ME_H1	ME_H2	ME_H1	ME_H2	ME_H1	ME_H2	ME_H1	ME_H2	ME_H1	ME_H2
hamp1/2_lag	.451	.344	.396	.258	.412	.209	.353	.128	0.365	0.242	.287	.152
primary	-.047	-.016	-.030	-.009	-.012	-.004	-.006	-.004	-.003	-.002	-.002	-.002
secondary	-.020	-.006	-.012	-.002	-.004	-.002	-.001	-.001	-.005	-.002	-.003	-.001
ln_inc_lag	-.016	-.005	-.008	-.002	-.016	-.002	-.011	-.001	-.00005	-.001	.001	-.001
selfemploy_lag	-.006	.003	-.006	.005	-.008	-.002	-.002	.002	.0005	.002	-.001	.002
unemployed_lag	.040	.023	.039	.028	.066	.012	.065	.019	.006	.006	.006	.006
retired_lag	.037	.012	.040	.017	.019	0.012	.022	.017	.014	.007	.013	.009
housework_lag	.067	.043	.066	.042	-.010	.002	.003	.007	.005	.006	.007	.008
inactive_lag	.003	.065	.015	.057	.261	.076	.137	.055	.079	.032	.047	.025

Table 4. Pooled Probit and Complementary log-log, marginal effects (Cont.)

	EL				E				P			
	PPM		CLL		PPM		CLL		PPM		CLL	
	ME_H1	ME_H2	ME_H1	ME_H2	ME_H1	ME_H2	ME_H1	ME_H2	ME_H1	ME_H2	ME_H1	ME_H2
hamp1/2_lag	.394	.257	.311	.159	.258	.122	.182	.069	.506	**.360**	.450	.267
primary	-.020	-.009	-.013	-.006	-.022	-.007	-.013	-.004	-.010	-.001	-.005	-.001
secondary	-.007	-.004	-.003	-.002	-.006	-.001	-.002	-.0001	.002	.00001	.003	.001
ln_inc_lag	-.006	-.004	-.003	-.002	-.011	-0.005	-.008	-.003	-.026	-.011	-.016	-.005
selfemploy_lag	-.004	.001	-.001	.005	-.013	.0004	.002	.002	.010	-.004	.014	.004
unemployed_lag	.036	.022	.040	.028	.042	.0174	.055	.023	.053	.035	.051	.043
retired_lag	.042	.041	.039	.047	.057	0.03	.067	.041	.089	.053	.068	.056
housework_lag	.027	.032	.029	.040	.048	.022	.058	.028	.056	.029	.050	.037
inactive_lag	.173	.154	.127	.125	.159	.086	.132	.085	.131	.096	.087	.085

Table 5. AIC, BIC and Reset test results

		AIC		BIC		Reset (p value)
DK	PPM	11974.16	H1 REM, H2 REM	12332.17	H1 REM, H2 REM	1.94 (.1638)
		4687.831		5045.839		16.20 (.000)
	REM	11430.54		11796.33		6.38 (.0115)
		4489.575		4855.366		12.14 (.0005)
	CLL	12005.84		12363.85		21.72 (.000)
		4776.912		5134.92		57.65 (.000)
NL	PPM	22664.2	H1 REM, H2 REM	23040.73	H1 REM, H2 REM	6.76 (.009)
		11826.28		12202.81		14.40 (.000)
	REM	21265.93		21650.82		3.01 (.0826)
		11263.23		11648.12		4.14 (.0418)
	CLL	22680.03		23056.56		16.34 (.000)
		11953.23		12329.76		68.12 (.000)
B	PPM	10453.37	H1 REM, H2 REM	10818.8	H1 REM, H2 REM	6.46 (.011)
		4941.878		5298.021		17.09 (.000)
	REM	9844.491		10217.87		5.56 (.0183)
		4699.404		5072.779		11.39 (.0007)
	CLL	10579.77		10945.2		71.99 (.000)
		5049.503		5405.646		70.90 (.000)
F	PPM	32187.85	H1 REM, H2 REM	32581.67	H1 REM, H2 REM	4.31 (.038)
		19136.92		19530.74		30.77 (.000)
	REM	30479.35		30881.92		1.24 (.265)
		18087.17		18489.74		22.78 (.000)
	CLL	32456.53		32850.35		132.69 (.000)
		19412.01		19805.83		147.30 (.000)
Irl	PPM	10681.61	H1 REM, H2 REM	11043.23	H1 REM, H2 REM	13.70 (.000)
		3810.951		4172.574		5.53 (.0187)
	REM	10258.49		10627.98		13.26 (.0003)
		3655.647		4025.131		5.40 (.0201)
	CLL	10816.73		11178.35		89.53 (.000)
		3867.635		4229.258		34.56 (.000)
I	PPM	28445.79	H1 REM, H2 REM	28863.29	H1 REM, H2 REM	.010 (.0748)
		13591.67		14009.17		51.11 (.000)
	REM	26696.04		27122.62		9.88 (.0017)
		12915.62		13342.2		38.31 (.000)
	CLL	28690.34		29107.84		136.55 (.000)
		13892.29		14309.79		199.74 (.000)
EL	PPM	26826.2	H1 REM, H2 REM	27226.25	H1 REM, H2 REM	32.13 (.000)
		16351.66		16751.72		17.62 (.000)
	REM	25719.52		26128.27		20.57 (.000)
		15828.11		16236.87		13.97 (.000)
	CLL	27070		27470.05		127.45 (.000)
		16498.67		16898.72		89.96 (.000)
E	PPM	31665.4	H1 REM, H2 REM	32073.21	H1 REM, H2 REM	157.97 (.000)
		16730.75		17138.56		99.65 (.000)
	REM	30182.55		30599.23		115.65 (.000)
		16036.45		16453.12		78.52 (.000)
	CLL	32270.23		32678.04		572.28 (.000)
		16996.33		17404.13		257.91 (.000)
P	PPM	34644.8	H1 REM, H2 REM	35050.55	H1 REM, H2 REM	34.37 (.000)
		22234.27		22640.01		70.42 (.000)
	REM	33055.27		33469.83		45.64 (.000)
		21439.23		21853.8		63.97 (.000)
	CLL	35085.77		35491.51		277.91 (.000)
		22582.71		22988.46		265.02 (.000)