Income, health and inequality trends in Europe

Tom Van Ourti* [a,b], Eddy van Doorslaer[b] and Xander Koolman[b]

Preliminary version – please do not quote

September 2005

[a] Department of Economics. University of Antwerp, Prinsstraat 13, 2000 Antwerp, Belgium

[b] Department of Health Policy & Management, Erasmus University, 3000 DR Rotterdam, The Netherlands.

*Corresponding author. Tel. +32-3-2204140, Fax: +32-3-2204585, E-mail: tom.vanourti@ua.ac.be.

Acknowledgements

This paper derives from the project "The dynamics of income, health and inequality over the life cycle" (known as the ECuity III Project), which is funded in part by the European Community's Fifth Framework Programme (contract QLK6-CT-2002-02297). We are grateful to the EC for financial support, to EUROSTAT for access to the ECHP data and to … for comments on an earlier version of this paper.

Abstract

Europe aims at combining income growth with a reduction in income and income-related health inequality. Theoretically, both aims can be reconciled only under very specific conditions for the type of growth and the income responsiveness of health. The paper checks whether these conditions held in Europe in the nineties using panel data from the *European Community Household Panel* surveys. Using pooled interval regressions and controlling for initial health, we find that (i) in all countries the income elasticity of health is positive and increases with income, and (ii) that income growth was not pro-rich in most EU countries, resulting in modest reductions in income inequality but little or no changes in income-related health inequality in the majority of countries.

JEL Classification: D30; D31; I10; I12

Keywords: income inequality, health inequality, income elasticity of health, Europe

1. Introduction

Among the fundamental objectives of the European Union are economic and social progress and improvements in living and working conditions. The EU leaders agreed in Lisbon in 2000 when setting strategic goals for the current decade, that the Union should strive for economic growth and to become “the most competitive and dynamic knowledge-based economy … with more and better jobs and greater social cohesion” (Atkinson et al, 2002). So, the Lisbon European Council not only aimed at stimulating economic growth but also to make a decisive impact on the eradication of income poverty and social exclusion and to monitor the progress towards these goals. One of the monitoring tools it created was the collection of new sets of comparable longitudinal household level data across all member states, like the *European Community Household Panel* (ECHP) survey, and its successor, the EU *Survey on Income and Living Conditions* (EU-SILC). Social exclusion in the EU is broadly defined and does not only refer to (lack of) income and employment but includes wider social dimensions like housing, education and health. A set of indicators has been developed for monitoring the degree of inequality in not only income but also social indicators like health status.[1]

An important question, therefore, is to what extent – and or under what conditions – the twin goals of income growth and reduction of social inequalities in health are compatible. A second – no less important – question is which countries have managed to achieve these

[1] Among the so-called Level 1 indicators – which consist of a restricted number of lead indicators covering the broad fields of social exclusion – are the ratio of equivalized income of the top and bottom quintile for income inequality (recommendation 15), and the same ratio for the proportion of the population classifying themselves in poor or very poor health (recommendation 23) in Atkinson et al (2002).

goals, and to what degree. Contoyannis and Forster (1999) have shown that, if the income elasticity of health rises with income, then (equiproportionate) income growth may lead to higher income-related health inequalities. If this were the case, then Europe may have to face a trade-off between these two goals. On the other hand, if growth goes hand in hand with a reduction in health inequality by income, then greater social inclusion may derive as a windfall profit. It turns out that the degree to which income growth occurs disproportionately at higher or lower incomes, and the degree to which health responds to income changes at varying income levels are both crucial elements for the relationship between income growth and inequality and the degree of income-related health inequality. The paper therefore aims to shed light on the empirically observed trends in income (inequality) and health (inequality) in European countries, and to test their consistency with the theoretical predictions of Contoyannis and Forster (1999). We do this by estimating static and dynamic models of health and by relating trends in income growth and income inequality to changes in income-related inequalities in health on the full 8 waves of the ECHP.

The paper is organised as follows. Section 2 explains how we have adopted the theoretical model of health behaviour of Contoyannis and Forster (1999) to guide our modelling strategy. Section 3 describes the ECHP data set and the empirical models used to test the model predictions. Empirical results on income elasticities of health and on empirical trends in income, health and inequality are presented in section 4, while section 5 provides a conclusion and discussion.

2. The relationship between the distributions of income and health

The theoretical model of health behaviour proposed by Contoyannis and Forster (1999) provides a theoretical basis for the analysis of variations in the distributions of income and health. Starting from a population of n individuals which are characterised by health levels ($h_i \geq 0$) and income levels ($y_i \geq 0$), they define an expected health function ($E\left(h_i \middle| y_i\right)$). The authors allow for a flexible functional form, i.e. the function and its slope are allowed to be increasing/decreasing with income. Theoretical predictions are derived for the effect of equiproportionate income growth on average population health ($E_y\left[E\left(h_i \middle| y_i\right)\right]$) and income-related inequalities in health. In line with earlier literature, they measure relative income inequality using Lorenz curves and Gini coefficients and income-related inequality in health using concentration curves and indices. They show that if the expected health function ($E\left(h_i \middle| y_i\right)$) is convex/concave/linear and increasing with income, then average health responds elastically/inelastically/unit elastically to equiproportionate income growth. In addition, they show that equiproportionate income growth, leads to lower/higher income-related inequalities in health if and only if the elasticity of expected health to income ($\varepsilon_{E\left(h_i \middle| y_i\right), y_i}$) is decreasing/increasing with income. While this result is powerful as it implies that income growth leads to a (welfare improving) average health increase and – depending on the slope of the elasticity of expected health to income – to a (welfare decreasing/increasing) increase/decrease in relative income-related inequality in health, it is of somewhat limited applicability as it only refers to equiproportionate income growth. The authors have limited their proposition to equiproportionate income growth since it allows isolating the effect of income growth from a change in income inequality. However, it is worth noting that the theoretical result also holds for pro-rich income growth if the elasticity of expected health to income is increasing with income and for pro-poor income growth if the elasticity of expected health to income is decreasing with income. Only when the elasticity of expected health to income is increasing/decreasing and growth is pro-poor/pro-rich, no unambiguous prediction can be made, *ceteris paribus*.

From previous research we know that the marginal effect of income on health is positive $\left(\frac{\delta E(h|y)}{\delta y}\rangle 0\right)$ and declining with income $\left(\frac{\delta^2 E(h|y)}{\delta y^2}\langle 0\right)$. Contrary to the intuition perhaps, this does not imply that the income elasticity of health $\left(\varepsilon_{E(h_i|y_i),y_i} = \frac{\partial E(h|y)}{\partial y}\frac{y}{E(h|y)}\right)$ reduces with income, i.e. that $\left(\frac{\partial \varepsilon}{\partial y} = \frac{\partial^2 E(h|y)}{\partial y^2}\frac{y}{E(h|y)} + \frac{\partial E(h|y)}{\partial y}\frac{1}{E(h|y)} < 0\right)$. One can see under what condition this expression will be positive: if the negative of the rate of change of the marginal effect is smaller than the marginal effect of income on health divided by income $\left(-\frac{\delta^2 E(h|y)}{\delta y^2}\langle\frac{\partial E(h|y)}{\partial y}\frac{1}{y}\right)$ then the income elasticity will be increasing with income. More intuitively, this means that as income increases, a change of one percent will mean a greater change in income that may offset the reduction of the marginal effect of income on health that accompanies a growth in income.

Our analysis has three objectives. First, empirical verification of the consequences of income growth requires obtaining estimates of the income elasticity of health and examining how these vary with rising income. Second, we will examine empirical trends in income inequality which, coupled with the elasticity estimates, allow us to make predictions on the evolution of income-related inequalities in health. Third, we will present evidence on the observed evolution in income-related inequalities in health.

3. Data and empirical model specification

The data used in this paper are taken from the full 8 waves (held in 1994-2001) of the *European Community Household Panel User Database* (ECHP-UDB). The ECHP was designed and coordinated by Eurostat, and it contains socioeconomic, demographic, health and health care utilisation variables, for a panel of households which only includes individuals aged 16 or older. It used a standardised questionnaire, which allows for cross-country comparisons as well as longitudinal analysis. We use all the information that is available for 13 EU member states: Austria, Belgium, Denmark, Finland, France, Germany, Greece, Ireland, Italy, Netherlands, Portugal, Spain and the United Kingdom. We decided not to analyze the data for Luxembourg (small sample) and Sweden (no panel data in ECHP). For Germany and the UK, we are not using the ECHP (which only ran from 1994 to 1997, i.e. waves 1 to 3) but instead used the *German Socio-economic Panel* (GSOEP) and the *British Household Panel Survey* (BHPS). Austria joined the survey in 1995 (wave 2) and in Finland only in 1996 (wave 3).

3.1 Estimating the elasticity of health with respect to income

The two key variables for this study are self-assessed health (SAH) and income. The ECHP income measure is disposable (i.e. after-tax) household income. Total household income includes all the net monetary income received by the household members during the *previous* year. It includes income from work (employment and self-employment), private income (from investments and property and private transfers to the household), pensions and other direct social transfers received. No account has been taken of indirect social transfers (e.g. reimbursement of medical expenses), receipts in kind and imputed rent from owner-occupied accommodation. We use this variable deflated (i) by yearly PPPs in euros – which is available in the ECHP (see Eurostat, 2003) – in order to allow for comparability across countries, and (ii) by the harmonised index of consumer prices (HICP), in order to allow for comparability across waves, i.e. in 1996 prices. The HICP is an overall indicator of price developments in the euro area and was taken from ECB (2000, 2003).[2] The income variable was further divided by the OECD modified equivalence scale in order to account for household size and composition (giving a weight of 1.0 to the first adult, 0.5 to the second and each subsequent person aged 14 and over, and 0.3 to each child aged under 4 in the household).

Self-assessed health is measured as the response to an ordered 5-point scale (ranging from very good to very poor) on the question "How is your health in general?" but we have adopted the scaling methods proposed by Van Doorslaer and Jones (2003) and used on the ECHP data by Van Doorslaer and Koolman (2004). Appropriate econometric analysis of an ordered categorical dependent variable, such as *SAH*, is typically based on the ordered probit or logit model but, if information on the scaling of the variable is available (i.e. values of the boundaries of the intervals are known), the interval (or grouped data) regression model provides a more efficient alternative to the ordered probit model (see e.g. Jones, 2000). We have used the empirical cumulative distribution function of HUI scores in the 1994 Canadian *National Population Health Survey* sample obtained in Van Doorslaer and Jones (2003) to scale the intervals of *SAH* for all European countries. This approach assumes that there is a stable mapping from HUI to the (latent) variable that determines reported *SAH* and that this applies not only to Canadian but also to European individuals. While the validity of this approach could be confirmed in the Canadian data (Van Doorslaer and Jones, 2003), it was not possible to test the external validity on the European data. Sensitivity analysis using other boundaries has shown that the results are almost identical when the imposed thresholds were derived from other (European) generic measures like the Euroqol (Lauridsen *et al*, 2004; Lecluyse and Cleemput, 2005).

[2] We do not use national CPI's since yearly PPP's already eliminate differences in the price evolution between countries. All that remains is a correction for 'average price evolution' in the euro area, i.e. the HICP.

We distinguish between a static and a dynamic version of our empirical model. For the estimation of the static interval health equations we have included as covariates – besides income and time dummies – only demographics like age and gender and level of education:

(1) $$h_{it}^{*} = x_{it}^{'}\alpha + \beta f\left(y_{it}\right) + d_{t}^{'}\delta_{t} + \varepsilon_{it}$$

where t denotes time, h_{it}^{*} is the latent health outcome, α, β and δ_t are parameters to be estimated, $f\left(y_{it}\right)$ is a function of income (see below), d_t is a set of time dummies, and $\varepsilon_{it} \sim N\left(0,\sigma_{\varepsilon}^{2}\right)$. We do not observe h_{it}^{*}, but we do observe SAH and boundaries derived from HUI scores. The vector of covariates (x_{it}) includes education and age dummies (categories: 16-29; 30-44; 45-59; 60-69; 70+) for both sexes. Education is measured as the highest level of general or higher education completed and available at three levels: recognised third level education (ISCED 5-7), second stage of secondary level of education (ISCED 3) and less than second stage of secondary education (ISCED 0-2). We limit the specification to these covariates on the grounds that these can safely be assumed to be exogenous for adults and that we are mainly interested here in a *causal* estimate of the overall income elasticity of health (utility), not in the endogenous variables (like life style or labour choices) that may mediate the effect of income on health. We have run pooled models on an unbalanced panel of individuals observed for (up to) 8 waves. Table 1 presents means of the variables used in the health equations for each country across all waves.

Table 1: Means of variables for each country

	Denmark	NL	Belgium	France	Ireland	Italy	Greece
sah (vbad=1)	4.158	3.869	3.875	3.585	4.229	3.687	4.119
male	0.487	0.471	0.467	0.475	0.495	0.494	0.472
age	45.72	45.37	46.99	47.08	44.75	44.12	48.03
higher educ	0.271	0.102	0.302	0.213	0.140	0.071	0.137
second educ	0.422	0.280	0.324	0.265	0.347	0.340	0.264
eqinc	15149	14223	15790	14189	12188	10822	8003
Observations	36272	70553	40410	86005	50234	121871	82739

	Spain	Portugal	Austria	Finland	Ger(SOEP)	UK(BHPS)
sah (vbad=1)	3.708	3.239	3.949	3.779	3.393	3.767
male	0.481	0.478	0.481	0.472	0.483	0.459
age	45.61	46.92	45.57	44.47	44.32	45.14
higher educ	0.159	0.050	0.058	0.283	0.184	0.384
second educ	0.177	0.104	0.592	0.396	0.543	0.133
eqinc	9561	7375	14790	12530	14683	14606
Observations	113784	89491	45211	37704	90563	67786

In addition to the covariates of the static model, the dynamic model includes SAH for the previous wave ($SAH_{i,t-1}$) and in the first wave ($SAH_{i,0}$). Both additional variables are included as sets of dummies for each category of SAH. Our specification bears some resemblance to those used in Hurd and Kapteyn (2003) and Contoyannis, Jones and Rice (2004) and is as follows:

$$(2) \qquad h_{it}^{*} = SAH_{i,t-1}^{'}\eta + SAH_{i,0}^{'}\chi + x_{it}^{'}\alpha + \beta f\left(y_{it}\right) + d_{t}^{'}\delta_{t} + \varepsilon_{it}$$

Compared to the static model, this specification captures state dependence and is, in effect, modelling income effects on health transitions. Moreover, it removes any correlation between income and initial health from β. We argue that, the inclusion of last year's and initial self-reported health attenuates reverse causation running from health to income. It results that the effect of income on current self-reported health is more likely to reflect a *causal* influence of income on health compared to the effect estimated in the static specification. The main disadvantage of the dynamic approach is that we loose one wave of data due to inclusion of lagged SAH. We also experimented with dynamic random effects panel models in which we parameterised the individual effects as a function of the means of time-varying variables and initial SAH (Chamberlain (1980), but prefer the pooled specifications as they impose less stringent exogeneity assumptions (see e.g. chapter 15 in Wooldridge, 2002). Moreover and reassuringly, the estimated β's resulting from random effects and pooled models are very similar.[3]

In view of the evidence in the literature on a non-linear relationship between income and individual health (Ecob and Smith, 1999; Gerdtham and Johannesson, 2000; Gravelle and Sutton, 2003; Mackenbach *et al.*, 2005) and its importance for the current paper (i.e. rising versus decreasing income elasticity), we have experimented with various specifications using logarithmic and polynomial transformations of income.[4] It should be noted that the income elasticity of health is constant with income in a logarithmic specification and can decrease/increase with an income polynomial. The choice between the logarithmic and polynomial transformation was based on (a combination of) two goodness-of-fit criteria: the Akaike Information Criterion (AIC) and the Bayesian Information Criterion (BIC). If both criteria preferred the same specification, then we only present results for the preferred model. When they conflicted, we present income coefficients for both, but estimated coefficients for all other variables for the specification with the lowest BIC. In most cases, the choice of the income transformation did not alter these, except for some minor changes in the education dummies for only a few countries.

[3] In the random effects models, we find that the coefficients on (initial) lagged SAH are (larger) smaller. This could result from the assumption of strict exogeneity, while the pooled models can cope with predetermined variables. Full results can be obtained from the authors.

[4] The order of the polynomial was determined by the following procedure. First, we estimated the model with a fifth order polynomial of income. Next, we consecutively reduced the order of the polynomial until an LR-test (1% significance level) rejected the 'reduced order' against the fifth order polynomial.

In estimating equations (1) and (2), we do not apply the Eurostat-provided cross-sectional individual sampling weights. If the intention is to estimate *causal* relationships – as we do with respect to the β's in equation (1) and (2) – estimation without sampling weights is consistent as long as sample selection, if any, is not depending on the dependent variable[5]. However, if the purpose of the exercise is to describe the data, one should use sampling weights in order to obtain better annual representativeness. The latter holds for the calculation of the elasticity of health with respect to income:

$$(3) \qquad \varepsilon_{E(h_{it}|y_{it},z_i),y_{it}} = \frac{\partial E\left(h_{it}\left|y_{it},z_i\right.\right)}{\partial y_{it}} \frac{y_{it}}{E\left(h_{it}\left|y_{it},z_i\right.\right)} = \hat{\beta}\frac{\partial f\left(y_{it}\right)}{\partial y_{it}} \frac{y_{it}}{E\left(h_{it}\left|y_{it},z_i\right.\right)}$$

where z_i includes all explanatory variables besides $f\left(y_{it}\right)$. In calculating equation (3), we use the overall (sampling) weighted mean of $E\left(h_{it}\left|y_{it},z_i\right.\right)$, estimate β without using sampling weights, and the other elements on the right hand side are evaluated at various values, i.e. (i) the overall weighted mean, and the weighted means of the incomes between (ii) 0^{th}-10^{th} percentile, (iii) 10^{th}-25^{th}percentile, (iv) 25^{th}-50^{th} percentile, (v) 50^{th}-75^{th} percentile, (vi) 75^{th}-90^{th} percentile, and (vii) 90^{th}-100^{th} percentile.

3.2 Estimating empirical trends in income inequality

We apply two methods to shed some light on trends in income inequality. First, we calculate the evolution of the weighted mean of income of the above-mentioned 7 income ranges. Second, we calculate the Gini index of income for each wave t ($G_{y,t} = \kappa_{1,t}$) using OLS-regression (see Kakwani *et al.* (1997) and Wagstaff and Van Doorslaer (2000)):

---

[5] We assume exogenous sample selection if any, since we cannot, for example, distinguish between attrition due to illness (endogenous) and attrition due to disease (exogenous). For additional discussion on this issue, see chapter 24 in Cameron and Trivedi (2005).

(4) $$2\sigma^2_{R^Y,t}\frac{y_{it}}{\bar{y}_t}\sqrt{w_{it}} = \sqrt{w_{it}}\kappa_{0,t} + \sqrt{w_{it}}\kappa_{1,t}R^Y_{it} + \eta_{it}$$

where an upper bar indicates a weighted average, w_{it} is the sampling weight of individual i in wave t, $\kappa_{0,t}$ and $\kappa_{1,t}$ are parameters to be estimated, η_{it} is an error term with mean zero, R^Y_{it} is the fractional rank of y_{it} in wave t, and $\sigma^2_{R^y,t} = \left[\sum_{i=1}^n w_{it}\right]^{-1}\left[\sum_{i=1}^n w_{it}\left(R^Y_{it} - 0.5\right)^2\right]$ is the weighted variance of R^Y_{it}. Kakwani *et al.* (1997) and Wagstaff and van Doorslaer (12) use the fractional income rank as proposed by Lerman and Yitzhaki (1989), i.e. $R^Y_{it} = \left(\sum_{i=1}^n w_{it}\right)^{-1}\left(\sum_{k=1}^{i-1} w_{kt} + 0.5w_{it}\right)$. Since different individuals can have the same income, we use a generalisation, namely $R^Y_{it} = \left[\sum_{i=1}^n w_{it}\right]^{-1}\left\{q\left(y_{it}-1\right) + 0.5\left[q\left(y_{it}\right) - q\left(y_{it}-1\right)\right]\right\}$ where $q\left(y_{it}\right) = \sum_k^n 1\left(y_{kt} \le y_{it}\right)w_{kt}$ equals the proportion of individuals with income y_{it} or less.

3.3 Estimating the evolution of income-related inequalities in health

We calculate the concentration index of health ($CI_t = \lambda_{1,t}$) for each wave t. This index takes values between -1 and +1. A positive (negative) value indicates pro-rich (pro-poor) income-related inequality in health. We start from equation (4), but replace income (y) with health (h):

(5) $$2\sigma^2_{R^Y,t}\frac{h_{it}}{\bar{h}_t}\sqrt{w_{it}} = \sqrt{w_{it}}\lambda_{0,t} + \sqrt{w_{it}}\lambda_{1,t}R^Y_{it} + \zeta_{it}$$

where $\lambda_{0,t}$ and $\lambda_{1,t}$ are parameters to be estimated and ζ_{it} is an error term with zero mean.

We use two estimates for h_{it}. First, since CI_t is only defined for continuous h, and since SAH is inherently categorical, we use the predicted values obtained from the dynamic model in equation (2). The resulting CI_t's can be interpreted as income-related inequalities in Health Utility. Second, the predicted values from equation (2) are partly determined by income as $f\left(y_{it}\right)$ is included in the set of covariates. Therefore, we perform a sensitivity analysis by computing CI_t's for SAH coded with the mid interval values of the Health Utility scores.

Summary statistics of the data used to calculate the Gini indices of income and the concentration indices of health are presented per country and wave in table 2. The number of included observations differs from those in the regression analysis (cf. Table 1) since all observations from the first wave are dropped due to the dynamic specification used to predict Health Utilities (see above). Note that – as for estimation of the health equations – we use an unbalanced panel. There it was argued that such an approach is feasible as long as there is no endogenous sample selection. In case of the Gini and concentration indices, our argument is that we are interested in the evolution of cross-section inequalities, not in the evolution of inequalities for a cohort. For example, if one were to use a balanced panel to investigate income-related inequalities in health, one would expect to observe an increase in inequalities if health declines faster and/or starts declining sooner for the lower – compared to the higher – socioeconomic groups (see e.g. Case and Deaton (2005)). However, the picture that emerges from a cross-section where births and deaths are included is likely to show a less increasing pattern.

Table 2: weighted mean *SAH* and equivalent income per country for analyzing trends

	Denmark	NL	Belgium	France	Ireland	Italy	Greece	Spain
wave 2								
sah (vbad=1)	4.142	3.871	3.857	3.567	4.176	3.672	4.053	3.689
eqinc	14274	13275	14608	13740	11657	10675	7580	8992
Observations	5011	8280	5216	11119	7198	15286	10995	14745
wave 3								
sah (vbad=1)	4.104	3.872	3.852	3.569	4.186	3.669	4.104	3.724
eqinc	14905	13685	15352	13685	11482	10903	7938	9368
Observations	4661	8441	5021	10896	6425	15467	10515	14104
wave 4								
sah (vbad=1)	4.126	3.864	3.858	3.544	4.211	3.688	4.031	3.703
eqinc	14812	14243	15116	14368	12288	10764	8195	9413
Observations	4277	8222	4693	10118	5973	14542	9861	13315
wave 5								
sah (vbad=1)	4.117	3.853	3.883	3.508	4.226	3.589	4.150	3.718
eqinc	15525	14577	15575	14587	12515	11222	8709	9526
Observations	3985	8182	4963	9904	5977	15123	9250	12814
wave 6								
sah (vbad=1)	4.120	3.832	3.889	3.542	4.259	3.589	4.151	3.730
eqinc	16327	14984	16127	14864	12448	11888	9363	10420
Observations	3799	7844	4683	9957	5216	14698	8858	12282
wave 7								
sah (vbad=1)	4.088	3.833	3.886	3.542	4.255	3.582	4.134	3.754
eqinc	16356	14408	16592	15042	12199	11798	9421	11179
Observations	3642	8011	4429	9430	4300	13967	8808	11588
wave 8								
sah (vbad=1)	4.069	3.822	3.897	3.538	4.266	3.616	4.195	3.743
eqinc	15789	15056	16813	15568	12971	11523	9164	11936
Observations	3609	7632	4047	9451	3857	12868	8890	11268

	Spain	Portugal	Austria	Finland	Ger(SOEP)	UK(BHPS)
wave 2						
sah (vbad=1)	3.689	3.266	NA	NA	3.261	3.802
eqinc	8992	7268	NA	NA	14303	13371
Observations	14745	10559	NA	NA	10891	7794
wave 3						
sah (vbad=1)	3.724	3.218	3.920	NA	3.289	3.787
eqinc	9368	7691	15000	NA	14443	13769
Observations	14104	10657	6562	NA	11292	7938
wave 4						
sah (vbad=1)	3.703	3.205	3.936	3.689	3.296	3.801
eqinc	9413	8009	14448	11290	14946	14571
Observations	13315	10663	6474	6458	11086	7930
wave 5						
sah (vbad=1)	3.718	3.222	3.933	3.667	3.303	3.771
eqinc	9526	8365	14441	11616	14865	15164
Observations	12814	10643	6177	5986	10846	8008
wave 6						
sah (vbad=1)	3.730	3.237	3.952	3.664	3.291	3.330
eqinc	10420	8786	15569	11873	15564	15003
Observations	12282	10658	5915	5868	10578	7964
wave 7						
sah (vbad=5)	3.754	3.236	3.973	3.669	3.297	3.750
eqinc	11179	9167	16473	12476	16494	16012
Observations	11588	10482	5515	4661	10374	7783
wave 8						
sah (vbad=5)	3.743	3.262	3.991	3.675	3.296	3.778
eqinc	11936	9660	15982	12695	16359	16488
Observations	11268	10476	5414	4676	10110	7630

4. Empirical findings

Full model estimation results of the preferred static and dynamic models are presented in Appendix Table A1 and A2, respectively. For the static model (Table 1), there were never any conflicts between the information criteria and the estimates include either a logarithmic or a polynomial transformation. For the dynamic model estimates (Table A2), coefficients for both income transformations are presented when criteria conflicted. In general, the coefficients for the age, gender and education dummies show the expected signs and magnitudes[6]. The same holds for the coefficients on lagged and initial self-reported health, which are supportive of state dependence.[7] Income coefficients were found to be (jointly) significant in all specifications and for all countries. In what follows we will concentrate on the estimated income elasticities of health (utility).

4.1 Income elasticity of health

A summary of the income elasticity estimates deriving from both the static and dynamic models is presented in Table 3, where countries are ranked by decreasing income elasticity from the dynamic model. The elasticity estimates from the static model indicate that they are positive and increasing with income in all countries (across most of the income range), except for Belgium and Ireland, for which the constant elasticity model was preferred. Unsurprisingly, all static model elasticity estimates are substantially higher than those estimated with the dynamic model, which really measure the short-run impact of income on annual health transitions. The dynamic model includes lagged and initial self-reported health, and thus its elasticities only reflect the impact of income on current health, but not the subsequent effect of lagged health on current health. The latter effect is implicitly included in

---

[6] Reference categories are M16-29, less than second stage of secondary education, wave 1 (or first available wave).

[7] Very good self-assessed health is the reference category.

the income elasticity resulting from the static models. We find that all elasticities resulting from the dynamic model are positive and in most cases increasing with income. Only for Denmark, Belgium and Ireland, the constant elasticity logarithmic model shows a better fit than the polynomial (see Table A.2). In a few more countries, the AIC and BIC conflict, but generally, the dynamic polynomial model estimates suggest that the income elasticity is increasing with income. This can be seen from the elasticity estimates at various parts of the income distribution. Only at the very high end, a decrease is sometimes observed. In general, it seems that we can fairly safely conclude that the income elasticity (both the static and dynamic) is positive and non-decreasing with income over most of the income range. Countries with particularly high income elasticity estimates include Portugal, Germany, France and the UK. Countries where health appears least income elastic include Finland, Belgium, Ireland and Italy.

Table 3: summary of income elasticity estimates

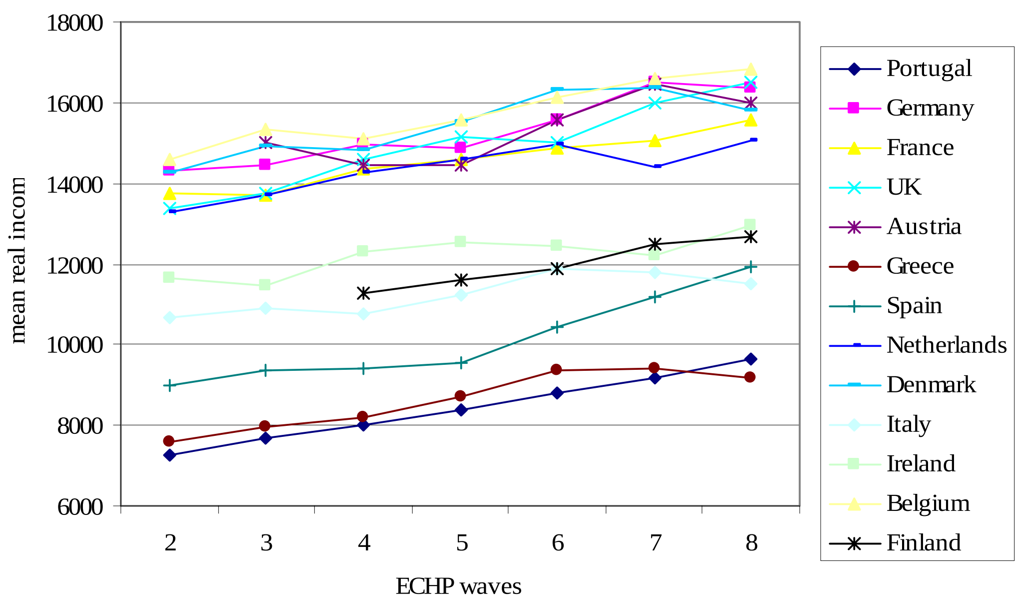
	Portugal	Germany	Francce	UK	Austria	Greece	Spain	NL	Denmark	Italy	Ireland	Belgium	Finland
static model													
elasticity at mean	0.0387	0.0290	0.0313	0.0296	0.0236	0.0178	0.0196	0.0159	0.0231	0.0132	0.0121	0.0110	0.0122
elasticity at 0-10	0.0133	0.0166	0.0158	0.0115	0.0150	0.0060	0.0069	0.0073	0.0120	0.0043			0.0060
elasticity at 10-25	0.0230	0.0245	0.0228	0.0185	0.0203	0.0108	0.0119	0.0111	0.0166	0.0080			0.0085
elasticity at 25-50	0.0311	0.0277	0.0277	0.0242	0.0228	0.0147	0.0157	0.0135	0.0203	0.0108			0.0104
elasticity at 50-75	0.0384	0.0291	0.0315	0.0302	0.0236	0.0180	0.0198	0.0162	0.0238	0.0137			0.0126
elasticity at 75-90	0.0427	0.0275	0.0324	0.0344	0.0217	0.0190	0.0227	0.0183	0.0267	0.0158			0.0147
elasticity at 90-100	0.0257	0.0142	0.0191	0.0316	0.0096	0.0109	0.0201	0.0180	0.0295	0.0163			0.0173
dynamic model													
elasticity at mean	0.0138	0.0120	0.0114	0.0102	0.0076	0.0076	0.0065	0.0057	0.0049	0.0038	0.0031	0.0022	0.0022
elasticity at 0-10	0.0044	0.0056	0.0056	0.0042	0.0047	0.0031	0.0025	0.0027		0.0011			0.0009
elasticity at 10-25	0.0076	0.0087	0.0080	0.0065	0.0064	0.0053	0.0042	0.0040		0.0021			0.0014
elasticity at 25-50	0.0106	0.0105	0.0099	0.0084	0.0073	0.0068	0.0054	0.0048		0.0030			0.0018
elasticity at 50-75	0.0137	0.0122	0.0115	0.0104	0.0076	0.0076	0.0066	0.0058		0.0040			0.0023
elasticity at 75-90	0.0164	0.0135	0.0123	0.0117	0.0071	0.0067	0.0072	0.0066		0.0049			0.0030
elasticity at 90-100	0.0139	0.0130	0.0091	0.0101	0.0023	-0.0001	0.0054	0.0066		0.0062			0.0045
elasticity at mean, ln-model		0.0090	0.0071	0.0073	0.0056	0.0052		0.0042					

Note: elasticity at mean is based on the polynomial model, except if the logarithm model is preferred. If AIC and BIC conflict, the constant elasticity resulting from the log model was added separately.

4.2 Trends in real incomes and in their inequality

The trends in income and income inequality in the ECHP[8] are summarized in Table A.3. First of all, it is obvious (see fig 1) that income growth has been unequal across European countries, and that there have been ups and downs in certain periods, but over the entire period, mean incomes have grown in *all* countries in real terms. Real growth was particularly strong (i.e. more than 20% in 6 years) in Spain, Greece, Portugal, and the UK. It is worth noting that the Contoyannis and Forster model predicts that real income growth, coupled with income elasticities rising with income, will, *ceteris paribus*, lead to rising income-related health inequality, *even if income inequality does not rise* (i.e. even with equiproportionate income growth).

Fig 1: Evolution of mean equivalent real income, 13 EU countries, 1994-2000

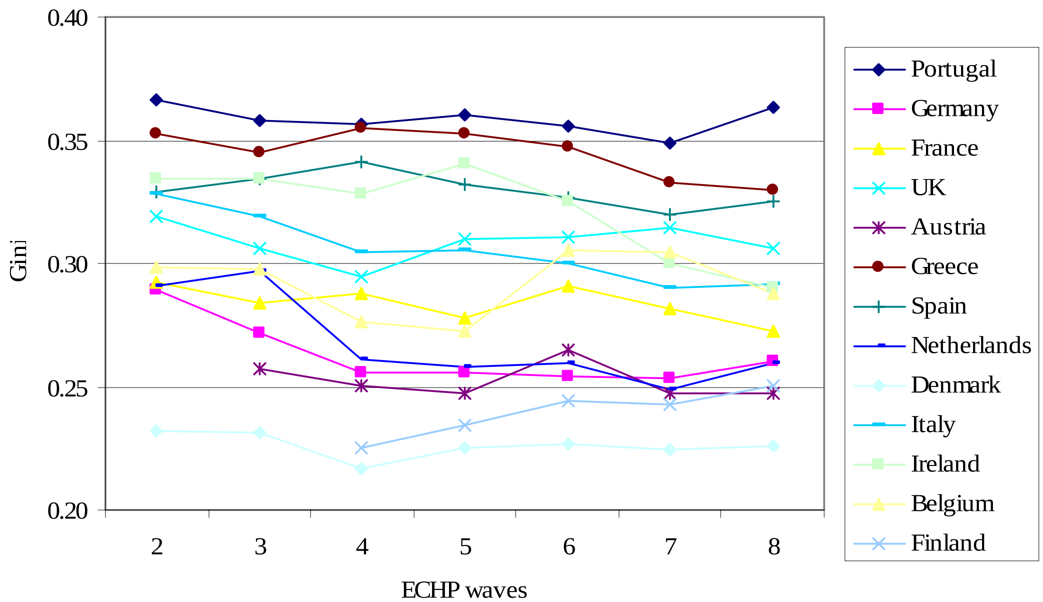


---

[8] We repeat that we use an unbalanced panel and apply sampling weights to improve *cross-section* representativity (see also section 3.3).

Second, the Gini trends make clear that very few countries show an increase in income inequality over the period 1994-2001. While the trends are by no means monotonic and while we did not test for statistical significance of any differences, it is clear from a visual inspection of Figure 2 that, on the whole, most countries have experienced either pro-poor income growth or income inequality has remained fairly stable. The sole exception is Finland which shows a clear increasing trend: its Gini index in 2001 was about 10 percent higher in 2001 than in 1996. For all other countries, the Gini tends to be lower at the end than at the beginning of the period, suggesting (slightly) pro-poor growth. This is more visible from the income evolutions at various income levels than from the Gini's (see table A.3): in almost all EU countries, mean incomes have grown faster at the bottom than at the top of the income distribution. In two countries, notably Denmark and Ireland, gains were greater for middle incomes. Only in one country, Finland, income growth was clearly higher at higher income levels. While these findings may be seen as somewhat surprising in view of the often reported rising relative income inequality over this period in the OECD context (see e.g. Smeeding, 2000; Moran, 2005; Kenworthy and Pontusson, 2005), they are consistent with earlier findings reported by Hildebrand and Van Kerm (2005) on the same data and with the series of cross sections compared in Atkinson (2003). For example, for the same period, also Atkinson (2003) reports stable Ginis for the Netherlands, Italy and the UK, a modest rise in Germany and a strong increase only in Finland.

Fig 2: Evolution of Gini index, 13 EU countries, 1994-2000



4.3 Trends in inequality in health by income

Given the estimated income elasticities and the trends in income growth and income inequality, unfortunately very few unambiguous predictions can be made on the basis of the propositions of Contoyannis and Forster (1999) presented in section 2. Only when pro-rich/pro-poor growth is coupled with an income elasticity that increases/decreases with income, the model predicts that income-related health inequality will grow/decrease. As we saw in sections 4.1 and 4.2, these conditions only held for the entire period in Finland. No consistent pro-rich growth was observed in any of the other countries. Figures 3 and 4 summarize the trends in the concentration indices for predicted health utility given by the dynamic model specifications. These figures and Table A4 show that the estimates based on the model with a polynomial transformation of income, do not differ very much from the estimates obtained from the model with a logarithmic transformation of income. While we regard these as our best estimates of income-related health inequality, these predicted levels are obviously partly income-predicted, which is why we compare these with the trends in CI's for HUI obtained from SAH coded with mean HUI levels. These are given in Figure A.1 (see also Table A.4) and show similar patterns.

We can observe that the concentration index for Finland has kept rising between waves 4 to 8, a pattern which is consistent with the theoretical predictions. Unfortunately, because for all other countries, the elasticity of health is rising with income, while income growth was pro poor, no unambiguous predictions can be made.

Fig 3: Concentration indices (polynomial transformation) 13 EU countries, 1995-2001

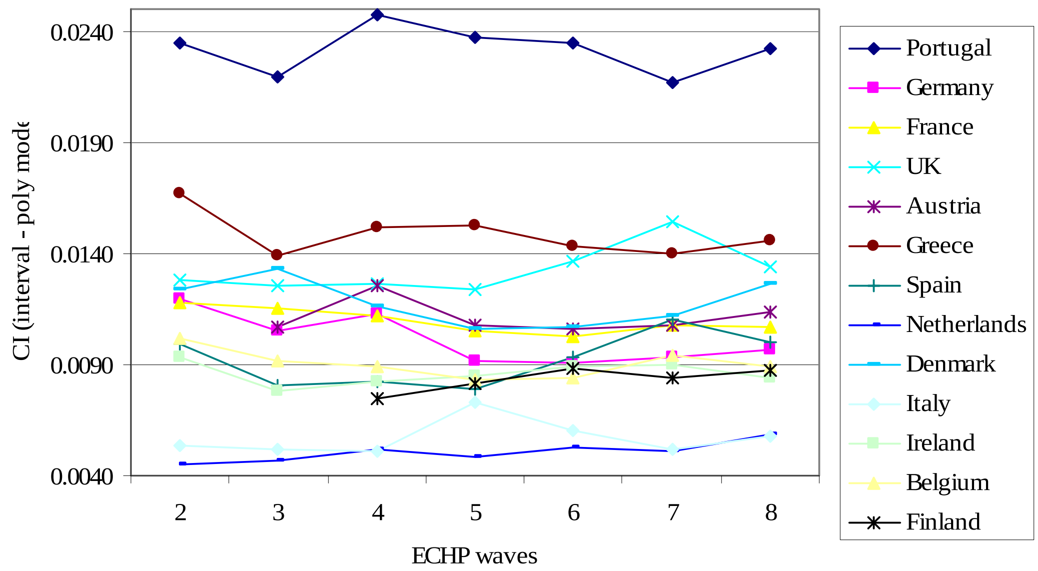
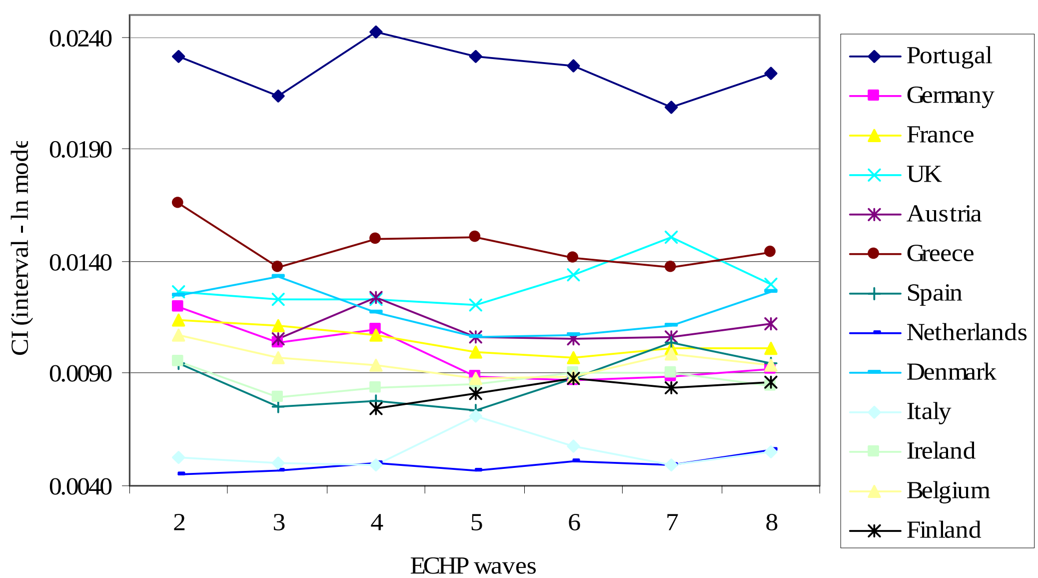


Figure 4: Concentration indices (log transformation) 13 EU countries, 1995-2001



5. Conclusion and discussion

In this paper we examined the usefulness of the Contoyannis and Forster (1999) framework for the analysis of trends in income-related health inequality in European countries using the Europanel (ECHP). Our findings are as follows. First, using both a static and a dynamic model on the pooled panels, we find that in all countries, both the long and short run marginal effect of income on health is positive and *decreasing* with income. In other words, the income-health relationship is concave, as expected. But secondly, and more importantly, in most countries, nonetheless the income elasticity of health is *rising* with income. The only exceptions are Belgium, Denmark and Ireland, for which a constant elasticity model was found to provide a better fit.

While over the 8 years of the panel, all countries were found to have experienced real income growth, in most countries this growth was not equally distributed across income levels. In most EU countries, income growth was found to be pro-poor, with higher growth rates at lower incomes and falling Gini coefficients. The only exceptions appear to be Denmark and Ireland (with pro-middle income growth) and Finland, with pro-rich growth. Given this combination of rising income elasticities with income and mostly pro-poor growth, no clear pattern of change in income-related health inequality can be predicted. Only for Finland, a steady rise in the concentration index of health can be observed.

We see several promising avenues for further research: First, we disregarded in this paper the effect of income growth on average population health. Giventhe concave relationship between health and income, average population health should increase with to equiproportionate income growth. Any pro-poor income growth should make this effect even stronger. Second, we could decompose the evolution of the concentration index into (i) a component reflecting the effect of the evolution of income inequality and (ii) a component measuring the effect of the elasticity of health with respect to income. Given the ambiguous predictions of the Contoyannis and Forster model in the case of a rising elasticity combined with pro-poor income growth, such decompositions may shed light on the outcomes in these ambivalent cases. Third, we should check whether the evolution in the Gini and concentration indices has statistical relevance.

References

Cameron A.C., Trivedi P.K. (2005) *Microeconometrics: methods and applications*, Cambridge University Press.

Case A, Deaton A. Broken down by work and sex: how our health declines. In: Wise A. (ed.), *Analyses in the Economics of Aging*, Chicago University Press, forthcoming.

Chamberlain G. (1980), Analysis of covariance with qualitative data. *Review of Economic Studies* 47: 225–238.

Contoyannis, P. and M. Forster (1999). The distribution of health and income: A theoretical framework, *Journal of Health Economics* 18: 605-622

Contoyannis, P. and M. Forster (1999). Our healthier nation?, *Health Economics* (1999) 8:289-296

Contoyannis, P., A.M Jones and N. Rice, 2004, The dynamics of health in the British Household Panel Survey, *Journal of Applied Econometrics* 19(4), 473-503

Crossley, T.F. and S. Kennedy, 2002, The reliability of self-assessed health status, *Journal of Health Economics*, 21, 643-658

ECB, 2000, *Monthly Bulletin December 2000*, European Central Bank.

ECB, 2003, *Monthly Bulletin January 2003*, European Central Bank.

Ecob R. and Smith G.D. (1999), Income and health: what is the nature of the relationship? *Social Science and Medicine* 48:693-705.

Eurostat, 2003, *ECHP UDB Description of variables: Data Dictionary*, *Codebook and Differences between Countries and Waves*, European Commission.

Gerdtham UG, Johannesson M (2000), Income-related inequality in life-years and quality-adjusted life-years. *Journal of health economics* 19(6): 1007-1026

Gravelle H, Sutton M (2003) Income related inequalities in self assessed health in Britain: 1979-1995. *Journal of Epidemiology Community Health* 57: 125-129.

Groot, W., 2000. Adaptation and scale of reference bias in self-assessments of quality of life. *Journal of Health Economics* 19(3), 403-420.

Hildebrand V, Van Kerm P (2005), Income inequality and self-rated health status: evidence from the European Community Household Panel, *mimeo*.

Hurd, M.D. and A. Kapteyn (2003): Health, Wealth and the Role of Institutions, *Journal of Human Resources* 38:2, pp. 386-415.

Kakwani N, Wagstaff A, van Doorslaer E. (1997), Socioeconomic inequalities in health: measurement, computation, and statistical inference. *Journal of econometrics* 77: 87-103.

Kenworthy, L. and J. Pontusson, 2005, *Rising inequality and the politics of redistribution in affluent countries*, LIS WP# 400, Luxembourg.

Lecluyse A, Cleemput I, 2005, Making health continuous: implications of different methods on the measurement of inequality. *Health Economics Letters*, forthcoming.

Lerman RI, Yitzhaki S (1989), Improving the accuracy of estimates of Gini coefficients. *Journal of Econometrics* 42: 43-47.

Mackenbach JP, Martikainen P, Looman CWN, Dalstra JAA, Kunst AE, Lahelma E, and members of the SEdHA working group (2005) The shape of the relationship between income and self-assessed health: an international study, *International Journal of Epidemiology* 34: 286-293.

Moran, TP, 2005, *Bootstrapping the LIS: statistical inference and patterns of inequality in the global North*, LIS WP nr. 378, Luxembourg.

Mills JA, Zandvakili S (1997), Statistical Inference via Bootstrapping for measures of Inequality, *Journal of Applied Econometrics* 12: 133-150.

Smeeding, T, 2002, *Globalization, inequality and the rich countries of the G-20: evidence from the Luxembourg Income Study*, LIS WP nr. 320, Luxembourg.

Van Doorslaer, E., Wagstaff, A., Bleichrodt, H., *et al*, 1997. Income-related inequalities in health: some international comparisons. *Journal of Health Economics* 16, 93-112.

Van Doorslaer, E and AM Jones, 2003, Inequalities in self-reported health: validation of a new approach to measurement, *Journal of Health Economics*, 22, 61-87

Van Doorslaer, E. & U. Gerdtham (2003), 'Does inequality in self-assessed health predict inequality in survival by income? Evidence from Swedish data', *Social Science & Medicine*, 2003, 57 (9): 1621-1629

Wagstaff, A., van Doorslaer, E., 1994. Measuring inequalities in health in the presence of multiple-category morbidity indicators. *Health Economics 3*, 281-291.

Wagstaff A, van Doorslaer E. (2000), Measuring and testing for inequity in the delivery of health care. *Journal of Human Resources* 35: 716-733.

Wooldridge J.M. (2002) *Econometric analysis of cross section and panel data*. The MIT Press.

Appendix Table 1: Static health equation estimates

	Denmark	NL	Belgium	France	Ireland	Italy	Greece	Spain	Portugal	Austria	Finland	Ger(SOEP)	UK(BHPS)
M30-44	-0.021**	-0.015**	-0.017**	-0.020**	-0.011**	-0.025**	-0.014**	-0.021**	-0.026**	-0.026**	-0.028**	-0.037**	-0.011**
M45-59	-0.042**	-0.033**	-0.036**	-0.048**	-0.024**	-0.056**	-0.042**	-0.049**	-0.069**	-0.067**	-0.063**	-0.090**	-0.029**
M60-69	-0.058**	-0.053**	-0.046**	-0.072**	-0.048**	-0.090**	-0.091**	-0.090**	-0.127**	-0.085**	-0.092**	-0.118**	-0.041**
M70+	-0.089**	-0.064**	-0.073**	-0.108**	-0.064**	-0.155**	-0.152**	-0.121**	-0.179**	-0.140**	-0.126**	-0.157**	-0.043**
F16-29	-0.006**	-0.012**	-0.009**	-0.009**	-0.001	-0.006**	-0.001	-0.004**	-0.001	-0.001	-0.006**	-0.009**	-0.010**
F30-44	-0.025**	-0.025**	-0.026**	-0.027**	-0.013**	-0.033**	-0.016**	-0.023**	-0.037**	-0.023**	-0.029**	-0.044**	-0.018**
F45-59	-0.053**	-0.042**	-0.045**	-0.059**	-0.024**	-0.067**	-0.052**	-0.064**	-0.098**	-0.062**	-0.063**	-0.101**	-0.036**
F60-69	-0.072**	-0.054**	-0.060**	-0.081**	-0.041**	-0.111**	-0.108**	-0.115**	-0.163**	-0.093**	-0.086**	-0.123**	-0.033**
F70+	-0.104**	-0.078**	-0.089**	-0.121**	-0.077**	-0.171**	-0.166**	-0.152**	-0.213**	-0.144**	-0.129**	-0.175**	-0.061**
higher education	0.030**	0.012**	0.020**	0.014**	0.016**	0.022**	0.018**	0.016**	0.019**	0.026**	0.026**	0.024**	0.018**
second education	0.021**	0.007**	0.012**	0.015**	0.013**	0.013**	0.014**	0.015**	0.015**	0.017**	0.011**	0.012**	0.012**
(eqinc/10000)	0.020**	0.015**		0.034**		0.015**	0.033**	0.027**	0.065**	0.032**	0.012**	0.035**	0.027**
(eqinc/10000)^2	-0.002**	-0.002**		-0.006**		-0.002**	-0.009**	-0.006**	-0.018**	-0.007**	-0.001**	-0.008**	-0.003**
(eqinc/10000)^3	0.000**	0.000**		0.000**		0.000**	0.001**	0.000**	0.002**	0.001**	0.000**	0.001**	0.000**
(eqinc/10000)^4				-0.000**			-0.000**	-0.000**	-0.000**	-0.000*		-0.000**	-0.000**
(eqinc/10000)^5				0.000**								0.000**	
ln(eqinc)			0.010**		0.011**								
wave_2	-0.001	0.001	0.004**	-0.005**	0.001	0.002**	0.009**	0.007**	-0.002+			0.001	-0.002+
wave_3	-0.005**	0.001	0.003*	-0.003**	0.002**	0.003**	0.016**	0.011**	-0.010**	0.001		0.002+	-0.004**
wave_4	-0.002	0.000	0.003**	-0.006**	0.004**	0.007**	0.012**	0.011**	-0.014**	0.003*	0.003**	0.004**	-0.006**
wave_5	-0.005**	0.005**	0.002	-0.010**	0.003**	0.000	0.017**	0.009**	-0.012**	0.003*	0.001	0.005**	-0.012**
wave_6	-0.007**	0.002+	0.003*	-0.004**	0.005**	0.000	0.017**	0.013**	-0.011**	0.006**	0.002*	0.002+	-0.058**
wave_7	-0.009**	0.003*	0.003*	-0.005**	0.005**	0.001	0.016**	0.013**	-0.012**	0.006**	0.002	0.001	-0.014**
wave_8	-0.010**	0.003*	0.004**	-0.007**	0.005**	0.005**	0.022**	0.011**	-0.012**	0.009**	0.003*	0.001	-0.011**
constant	0.916**	0.913**	0.830**	0.877**	0.835**	0.910**	0.921**	0.896**	0.874**	0.905**	0.915**	0.864**	0.883**
Sigma	0.084**	0.065**	0.073**	0.112**	0.065**	0.085**	0.094**	0.091**	0.113**	0.083**	0.067**	0.114**	0.101**
Observations	36272	70553	40410	86005	50234	121871	82739	113784	89491	45211	37704	90563	67786

Notes: Robust z statistics in parentheses. + significant at 10%; * significant at 5%; ** significant at 1%; eqinc: equivalent income

Appendix Table 2: Dynamic health equation estimates

	Denmark	NL	Belgium	France	Ireland	Italy	Greece	Spain	Portugal	Austria	Finland	Germany	UK
sah good lag	-0.020**	-0.018**	-0.020**	-0.016**	-0.018**	-0.020**	-0.021**	-0.009**	-0.015**	-0.020**	-0.018**	-0.020**	-0.025**
sah fair lag	-0.072**	-0.060**	-0.066**	-0.059**	-0.061**	-0.055**	-0.073**	-0.046**	-0.061**	-0.063**	-0.059**	-0.063**	-0.068**
sah bad lag	-0.181**	-0.144**	-0.159**	-0.153**	-0.138**	-0.160**	-0.159**	-0.120**	-0.183**	-0.159**	-0.138**	-0.149**	-0.145**
sah vbad lag	-0.358**	-0.290**	-0.284**	-0.275**	-0.221**	-0.339**	-0.298**	-0.208**	-0.362**	-0.320**	-0.209**	-0.320**	-0.296**
sah good initial	-0.012**	-0.009**	-0.011**	-0.009**	-0.008**	-0.008**	-0.005**	-0.005**	-0.003**	-0.009**	-0.011**	-0.012**	-0.013**
sah fair initial	-0.034**	-0.032**	-0.033**	-0.034**	-0.028**	-0.021**	-0.018**	-0.028**	-0.018**	-0.028**	-0.033**	-0.035**	-0.039**
sah bad initial	-0.068**	-0.071**	-0.067**	-0.077**	-0.071**	-0.062**	-0.042**	-0.075**	-0.051**	-0.068**	-0.076**	-0.072**	-0.083**
sah vbad initial	-0.092**	-0.121**	-0.147**	-0.139**	-0.102**	-0.093**	-0.074**	-0.129**	-0.092**	-0.113**	-0.118**	-0.134**	-0.138**
M30-44	-0.005**	-0.005**	-0.005**	-0.008**	-0.004**	-0.007**	-0.004**	-0.009**	-0.008**	-0.008**	-0.008**	-0.011**	-0.006**
M45-59	-0.010**	-0.010**	-0.010**	-0.018**	-0.009**	-0.018**	-0.014**	-0.018**	-0.024**	-0.020**	-0.017**	-0.030**	-0.011**
M60-69	-0.013**	-0.016**	-0.013**	-0.024**	-0.015**	-0.032**	-0.030**	-0.032**	-0.042**	-0.024**	-0.024**	-0.037**	-0.015**
M70+	-0.029**	-0.023**	-0.025**	-0.044**	-0.022**	-0.061**	-0.059**	-0.048**	-0.062**	-0.053**	-0.038**	-0.060**	-0.021**
F16-29	-0.001	-0.003**	-0.003*	-0.001	0.001	-0.002**	0.000	-0.002**	-0.001	-0.001	-0.002*	0.000	-0.002
F30-44	-0.007**	-0.007**	-0.007**	-0.010**	-0.003**	-0.011**	-0.005**	-0.010**	-0.013**	-0.008**	-0.009**	-0.010**	-0.006**
F45-59	-0.015**	-0.014**	-0.012**	-0.019**	-0.007**	-0.023**	-0.015**	-0.023**	-0.032**	-0.019**	-0.017**	-0.032**	-0.014**
F60-69	-0.018**	-0.018**	-0.014**	-0.026**	-0.012**	-0.038**	-0.035**	-0.040**	-0.049**	-0.028**	-0.022**	-0.036**	-0.013**
F70+	-0.031**	-0.028**	-0.029**	-0.043**	-0.026**	-0.064**	-0.058**	-0.059**	-0.070**	-0.053**	-0.043**	-0.062**	-0.027**
higher education	0.008**	0.004**	0.006**	0.005**	0.005**	0.006**	0.006**	0.005**	0.004**	0.007**	0.008**	0.008**	0.008**
second education	0.006**	0.002*	0.003**	0.004**	0.004**	0.004**	0.005**	0.005**	0.003**	0.005**	0.003*	0.005**	0.003*
(eqinc/10000)		0.005**		0.011**		0.004**	0.017**	0.010**	0.020**	0.009**	0.002**	0.010**	0.009**
(eqinc/10000)^2		-0.001**		-0.002**		-0.000**	-0.006**	-0.002**	-0.004**	-0.002**		-0.001**	-0.001**
(eqinc/10000)^3		0.000**		0.000**			0.001**	0.000**	0.000**	0.000**		0.000**	0.000**
(eqinc/10000)^4				-0.000**			-0.000**	-0.000**				-0.000**	-0.000**
ln(eqin)	0.004**	0.004**	0.002**	0.006**	0.003**		0.005**			0.005**		0.007**	0.006**
wave_3	-0.004*	0.001	-0.002+	0.002	0.001	-0.001	0.001	0.003*	-0.006**			0.000	-0.001
wave_4	0.001	0.000	-0.002+	-0.001	0.002*	0.002**	-0.006**	0.000	-0.006**	0.001		0.001	-0.001
wave_5	-0.003*	0.000	-0.004**	-0.004**	0.001	-0.004**	-0.001	-0.003**	-0.003*	0.000	-0.002*	0.000	-0.005**
wave_6	-0.004**	-0.002+	-0.003**	0.001	0.003**	-0.003**	-0.001	0.002+	-0.003*	0.002*	-0.002*	-0.002+	-0.050**
wave_7	-0.005**	-0.001	-0.002*	-0.001	0.001	-0.003**	-0.003**	0.000	-0.006**	0.002	-0.003*	-0.002	0.015**
wave_8	-0.006**	-0.001	-0.002*	-0.003*	0.002*	0.000	0.003*	-0.001	-0.005**	0.004**	-0.001	-0.004**	-0.002
Constant	0.919**	0.919**	0.940**	0.886**	0.931**	0.950**	0.925**	0.939**	0.926**	0.911**	0.954**	0.875**	0.898**
Sigma	0.062**	0.050**	0.054**	0.088**	0.052**	0.065**	0.076**	0.074**	0.082**	0.063**	0.052**	0.088**	0.081**

Observations	28984	56612	33052	70875	38946	101951	67177	90116	74138	36057	27649	75177	55644
Log likelihood poly	-41564	-69777	-42377	-112146	-51353	-136792	-106097	-135104	-97783	-50938	-33020	-109753	-88328
Log likelihood ln	-41564	-69782	-42372	-112162	-51351	-136799	-106105	-135125	-97809	-50940	-33022	-109761	-88336
AIC poly	83182	139611	84806	224350	102763	273638	212253	270266	195622	101930	66088	219564	176714
AIC ln	83179	139616	84795	224375	102754	273651	212261	270301	195669	101930	66092	219573	176725
BIC poly	83406	139861	85025	224616	103003	273895	212517	270539	195880	102159	66285	219832	176973
BIC ln	83394	139849	85014	224613	102977	273898	212498	270546	195909	102143	66290	219813	176957

Notes: Robust z statistics in parentheses. + significant at 10%; * significant at 5%; ** significant at 1%. poly: polynomial; ln: natural logarithm; eqinc: equivalent income

Appendix Table 3: Income growth income inequality (ratio of wave x to wave 2)

	Portugal	Germany	France	UK	Austria	Greece	Spain	Netherlands	Denmark	Italy	Ireland	Belgium
mean eqinc for 0-10 in wave 3	123.09	120.35	106.87	109.17	NA	106.45	100.85	103.85	102.79	105.10	100.03	111.91
mean eqinc for 10-25 in wave 3	111.90	103.61	101.10	105.53	NA	108.93	105.20	101.15	104.49	104.40	97.18	107.01
mean eqinc for 25-50 in wave 3	105.09	103.31	100.61	104.96	NA	105.97	103.86	101.73	104.51	103.92	99.19	104.67
mean eqinc for 50-75 in wave 3	105.22	100.45	99.21	104.00	NA	105.28	102.76	102.60	105.43	103.09	98.81	103.44
mean eqinc for 75-90 in wave 3	104.24	101.26	99.32	103.23	NA	103.55	102.09	103.20	104.86	101.21	96.50	103.05
mean eqinc for 90-100 in wave 3	105.15	96.27	97.86	98.78	NA	103.20	107.74	105.29	102.99	99.44	99.57	107.61
mean eqinc in wave 3	105.83	100.98	99.59	102.97	NA	104.72	104.18	103.09	104.42	102.14	98.50	105.09
Gini index wave3	97.64	93.96	97.09	95.99	NA	97.86	101.56	102.21	99.69	97.15	100.11	99.72
mean eqinc for 0-10 in wave 4	130.76	142.04	104.96	125.96	98.44	107.22	95.30	132.19	104.17	109.55	108.52	117.36
mean eqinc for 10-25 in wave 4	117.07	111.88	106.21	114.68	96.64	107.90	100.95	111.07	105.61	106.41	105.33	109.00
mean eqinc for 25-50 in wave 4	111.11	108.35	105.28	112.71	97.47	107.77	103.48	111.16	105.80	104.37	108.16	105.42
mean eqinc for 50-75 in wave 4	108.09	103.67	104.97	110.35	96.74	107.54	103.96	108.77	107.07	103.66	105.82	104.19
mean eqinc for 75-90 in wave 4	107.56	102.05	104.72	108.16	97.16	107.57	105.43	107.40	105.87	100.97	102.66	103.47
mean eqinc for 90-100 in wave 4	110.32	97.23	102.73	101.81	93.06	109.49	107.62	97.85	94.73	92.54	105.23	97.41
mean eqinc in wave 4	110.20	104.49	104.57	108.97	96.32	108.11	104.68	107.29	103.77	100.84	105.42	103.48
Gini index wave4	97.12	88.34	98.38	92.30	97.31	100.69	103.65	89.75	93.49	92.87	98.24	92.61
mean eqinc for 0-10 in wave 5	139.73	142.51	113.96	120.74	99.75	115.54	101.59	134.75	102.75	121.13	106.46	124.51
mean eqinc for 10-25 in wave 5	122.96	111.38	109.14	115.60	97.61	116.66	105.50	115.22	107.10	112.51	106.34	113.06
mean eqinc for 25-50 in wave 5	114.57	107.35	108.16	115.18	97.78	114.56	105.61	114.42	111.18	107.32	110.45	108.96
mean eqinc for 50-75 in wave 5	110.98	102.58	106.89	113.50	96.82	114.29	105.71	111.27	112.67	107.18	104.55	107.39
mean eqinc for 75-90 in wave 5	112.72	102.35	106.42	113.36	96.39	113.92	106.61	109.90	111.98	104.77	99.86	107.52
mean eqinc for 90-100 in wave 5	117.32	96.70	101.35	110.54	92.55	116.06	106.23	99.23	100.61	97.81	114.83	98.85
mean eqinc in wave 5	115.10	103.92	106.16	113.41	96.27	114.90	105.93	109.80	108.77	105.12	107.36	106.62
Gini index wave5	98.25	88.48	95.10	97.01	96.08	100.14	100.87	88.65	97.12	92.95	101.95	91.14
mean eqinc for 0-10 in wave 6	156.96	152.74	113.90	120.14	100.76	132.32	118.67	134.09	106.88	135.83	103.71	122.28
mean eqinc for 10-25 in wave 6	129.35	118.39	108.89	115.14	103.43	128.05	114.49	118.42	114.06	120.70	108.08	112.52
mean eqinc for 25-50 in wave 6	121.72	111.25	108.29	114.21	103.13	124.65	117.50	117.93	116.59	115.12	113.26	108.44
mean eqinc for 50-75 in wave 6	115.86	107.73	107.47	111.71	102.38	121.78	116.23	114.91	117.46	112.69	106.58	105.32
mean eqinc for 75-90 in wave 6	116.97	107.14	106.04	110.41	101.61	121.73	114.73	112.42	117.48	109.67	103.24	104.55
mean eqinc for 90-100 in wave 6	123.82	100.77	109.66	111.02	108.76	124.43	115.49	102.31	107.18	103.55	105.87	120.04
mean eqinc in wave 6	120.90	108.81	108.17	112.20	103.79	123.52	115.88	112.87	114.38	111.36	106.79	110.40
Gini index wave6	96.96	87.93	99.43	97.22	102.94	98.63	99.21	89.17	97.66	91.48	97.34	102.17

Note: income inequality in wave 2 equals 100

Appendix Table 3 (continued)

	Portugal	Germany	France	UK	Austria	Greece	Spain	Netherlands	Denmark	Italy	Ireland	Belgium
mean eqinc for 0-10 in wave 7	162.30	167.61	117.72	124.59	117.08	144.56	137.41	136.86	106.44	137.65	101.41	129.11
mean eqinc for 10-25 in wave 7	135.06	124.99	110.09	122.50	112.40	132.47	126.22	115.21	114.35	122.58	108.62	115.32
mean eqinc for 25-50 in wave 7	128.22	118.36	111.16	122.05	111.13	127.80	126.32	114.50	117.67	116.85	116.97	111.12
mean eqinc for 50-75 in wave 7	125.32	113.17	110.17	118.08	109.52	124.87	123.82	111.16	118.06	112.34	109.80	107.56
mean eqinc for 75-90 in wave 7	122.90	112.74	110.18	116.81	108.28	122.99	122.91	109.10	117.41	107.97	101.52	109.43
mean eqinc for 90-100 in wave 7	123.55	107.91	105.22	121.04	107.74	118.67	121.98	94.25	106.42	99.97	93.71	122.43
mean eqinc in wave 7	126.14	115.32	109.47	119.75	109.82	124.29	124.31	108.54	114.59	110.52	104.65	113.58
Gini index wave7	95.10	87.80	96.39	98.44	96.09	94.39	97.25	85.53	96.82	88.52	89.83	102.05
mean eqinc for 0-10 in wave 8	174.22	166.81	121.31	131.80	109.99	145.36	136.37	136.59	103.03	132.42	109.11	138.90
mean eqinc for 10-25 in wave 8	140.26	121.34	117.91	128.39	110.43	129.57	132.93	118.31	109.98	117.48	116.63	118.68
mean eqinc for 25-50 in wave 8	129.21	116.30	116.86	126.13	107.78	124.22	135.16	117.58	112.68	114.69	128.67	114.84
mean eqinc for 50-75 in wave 8	128.33	111.45	114.73	123.51	106.66	122.52	133.09	116.32	114.38	110.16	117.92	112.06
mean eqinc for 75-90 in wave 8	127.78	111.68	113.60	121.75	105.43	119.67	129.18	113.19	113.94	105.31	108.00	114.19
mean eqinc for 90-100 in wave 8	138.72	110.16	105.60	119.82	103.98	114.02	133.25	102.34	102.67	97.77	95.97	115.31
mean eqinc in wave 8	132.92	114.37	113.30	123.31	106.55	120.90	132.73	113.42	110.61	107.95	111.28	115.09
Gin index wave8	99.10	89.95	93.20	95.86	95.94	93.58	98.79	89.20	97.45	88.97	86.68	96.36

Note: income, inequality in wave 2 equals 100

Appendix Table 4: Income-related inequality in health (ratio of wave x to wave 4)

	Portugal	Germany	France	UK	Austria	Greece	Spain	Netherlands	Denmark	Italy	Ireland	Belgiu
Mid interval health utility												
wave 2	87.0791	103.1917	119.1154	103.3664	NA	104.1928	114.0608	81.9058	130.2599	111.2220	88.0346	119.27
wave 3	92.8008	103.7698	110.2549	95.0525	81.0749	82.3449	99.2024	86.6903	117.4864	115.6160	97.8123	117.65
wave 4	100.0000	100.0000	100.0000	100.0000	100.0000	100.0000	100.0000	100.0000	100.0000	100.0000	100.0000	100.00
wave 5	89.5078	115.4956	112.8205	99.5248	79.9109	93.0221	112.1162	105.8360	98.8411	136.0601	105.3163	104.35
wave 6	94.5011	77.4649	107.3372	173.7777	92.8671	83.6976	101.4102	126.6263	98.3472	109.6663	99.3214	94.30
wave 7	83.1450	83.7881	104.5213	102.0671	83.1566	87.8467	138.1989	120.7737	115.9928	113.5874	98.3531	119.64
wave 8	86.0338	79.4602	116.0408	102.5694	98.6325	82.8128	123.6116	115.4312	130.0257	103.3989	112.2394	110.48
Health utility from dynamic log model												
wave 2	95.7664	108.5201	106.0374	102.3916	NA	110.6893	122.1858	90.1941	106.8703	105.7900	113.8220	113.72
wave 3	88.5167	94.4934	103.7245	99.7020	84.9291	91.7731	97.3391	92.7470	114.0851	101.0928	94.7636	103.45
wave 4	100.0000	100.0000	100.0000	100.0000	100.0000	100.0000	100.0000	100.0000	100.0000	100.0000	100.0000	100.00
wave 5	95.6102	80.8271	92.8066	98.0719	85.6311	100.8128	94.8471	92.8932	91.0333	142.9526	102.1783	93.51
wave 6	94.0852	79.4445	90.8386	108.8621	84.9308	94.1419	113.5072	101.9026	91.6820	115.7819	108.2540	94.31
wave 7	86.4415	80.8262	94.3775	122.5924	86.1807	91.7303	133.9301	97.9671	95.4980	99.4748	108.5175	105.42
wave 8	92.5652	83.7436	94.4397	105.6796	90.9721	95.7873	122.0462	112.3037	108.2173	112.2506	101.1016	100.02
Health utility from dynamic polynomial												
wave 2	94.7364	105.8657	105.4146	100.9740	NA	110.4777	120.7580	87.6803	106.6982	104.9549	113.5642	113.94
wave 3	88.4032	93.4935	103.6741	99.0087	85.0679	91.8553	97.5156	91.3573	114.3159	100.8389	94.1161	103.39
wave 4	100.0000	100.0000	100.0000	100.0000	100.0000	100.0000	100.0000	100.0000	100.0000	100.0000	100.0000	100.00
wave 5	95.6784	81.1732	94.2491	98.0457	85.8692	100.6405	95.3896	93.8814	91.1333	142.3738	102.3232	93.25
wave 6	94.6602	80.5747	92.2019	108.2961	84.8280	94.3885	113.5453	102.3981	92.2074	117.3216	108.2966	94.06
wave 7	87.5829	82.4926	96.1356	121.8764	86.0469	92.3361	133.3053	98.9119	95.9879	101.2046	108.7036	106.07
wave 8	93.7726	85.4806	95.9668	106.0082	90.8318	96.3853	121.8428	113.0394	108.6088	113.1690	101.5488	100.46

Figure 4: Concentration indices (HUI mid interval transformation) 13 EU countries, 1995-2001