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"TRENDS IN INCOME INEQUALITY IN THE EUROPEAN UNION: IMPLICATIONS FOR HEALTH INEQUALITIES"

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ABSTRACT

The comparative analysis of income inequality across countries has acquired increasing importance in recent years. This paper is divided in two parts. The first one is focused on the analysis of income inequality in the European Union. To carry out this task, we use different models based on Lorenz curves and quantiles functions and different equivalence scales. The European Community Household Panel Data are used. The second part of the paper is focused on explaining the differences in income and health inequalities across European countries. In particular several hypotheses concerning the economic determinants of health inequalities are studied.

KEY WORDS: Income inequality, Lorenz curves, quantile functions, equivalence scales, European Community Household Panel, health inequalities

JEL Classification codes: D63, I1, I10, I32

1. INTRODUCTION

In recent studies about the relationship between income inequality and health two hypotheses have been proposed: The absolute income hypothesis and the relative income hypothesis (Gravelle *et al.,* 2002 and 2003; Wildman, 2003; Lopez Casasnovas and Rivera, 2002; Eberstadt and Satel, 2004). The absolute income hypothesis states that the higher an individual's income the better is their health, holding other factors constant (Preston, 1975). Thus, individual health is a function of individual income. On the other hand, the relative income hypothesis states that, in developed countries, individual's health is also affected by the distribution of income within society (Kawachi *et al*., 1996; Wilkinson, 1996 and Waldmann, 1992). In this way, income inequality has a larger impact on individual health than absolute income in developed countries. Both hypotheses have been tested empirically in recent papers. These studies suggest that reducing inequality is good for the health of the whole population and not only for those individuals with the lowest incomes.

To test these hypotheses, we have used the new information contained in the European Community Household Panel (ECHP) released by the European Commission's Statistical Office (EUROSTAT). This survey contains data homogeneous across countries making comparisons possible. Also, we have used health indicators taken from the Organisation for Economic Development and Cooperation (OECD) Health Data.

The paper is organised as follows. Section two describes the data sources we have used and characteristics of the variables involved in our analysis together with the principal methodological decisions we have taken. In section three, population functions, inequality measures and estimation methods are studied. In section four, we examine the empirical evidence between income inequality and health based on aggregated data. In section five, we present empirical results and finally, section six gives a summary and conclusion.

2. THE EUROPEAN COMMUNITY HOUSEHOLD PANEL: METHODOLOGICAL DECISIONS

This survey contains data on individuals and households for the European Union countries with eight waves available (1994-2001). The main advantage is that information is homogeneous among countries since the questionnaire is similar across them. This source of data is coordinated by the Statistical Office of the European Communities (EUROSTAT). Also, this survey includes rich new information about income, education, employment, health, etc. In this sense, it is important to highlight that it is the first fixed and harmonized panel for studying socio-economic factors of the households and individuals inside the European Union.

This representative survey of households of different European Union countries was carried out for the first time in 1994 and were interviewed 60.500 households (approximately 170.000 individuals) for the 12 Member States[1]. For example, in the case of Spain the first wave was of 7.200 households (approximately 23.000 individuals). In this paper, we have used the microdata for the European Union countries in order to test the sensibility and robustness of the results to different hypotheses.

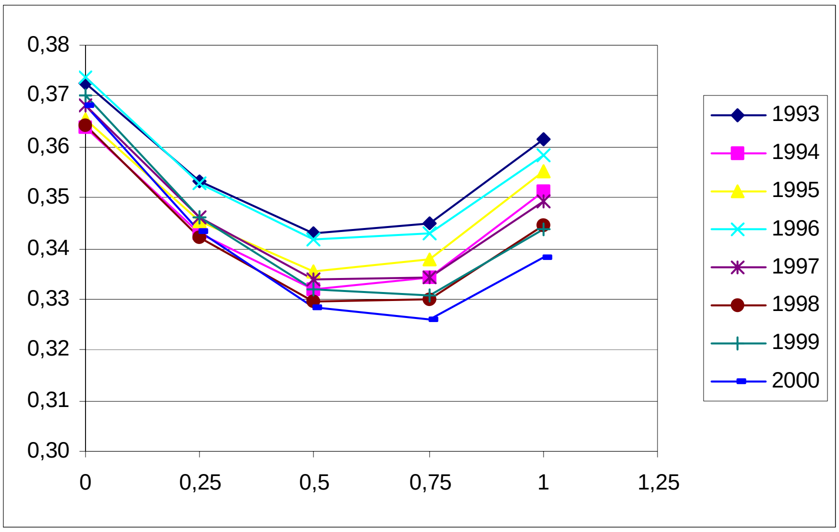
The total net income of each household is available and it covers the total income received by all the member of the household from all sources. However, comparisons among countries can be made in equivalent units taking into account differences in the national currency purchasing power[2].

The income measure is disposable (after tax) household income per equivalent adult. For the interpretation of statistical data on income distribution it is important to define the *income unit* upon which measurement is to be based. The reference period of income is the year prior to interview. The interviews corresponding to the first eight waves of the ECHP were perfomed in the years 1994, 1995, 1996, 1997, 1998, 1999, 2000 and 2001, meaning that the corresponding incomes refer to, respectively, the years 1993, 1994, 1995, 1996, 1997, 1998, 1999 and 2000. We have used household information rendering the component family by using equivalence scales. The heterogeneity of the households has been approached using the specification given by Coulter *et al.* (1992) that summarize different equivalence scales through a single parameter supposing that this scale only depends on the number of members of the household. According with this method, the "*equivalent income*", Y_h, of a household with n_h members and with income without adjusting X_h is:

$$Y_h = \frac{X_h}{n_h^s}. \tag{1}$$

The parameter "*s*" lies between zero to one. When s=1, we obtain the distribution of *income per individual*. When s=0 we obtain *income per household*. Also, the sensitivity of the results has been analysed estimating the inequality for different values of parameter "*s*". In particular, we have considered s =0, 0.25, 0.5, 0.75, and 1. Parameter "*s*" can be interpreted as a measure of economies of scale within the household. Figure 1 shows the sensitivity of the Gini index to parameter "s" in Spain. This pattern is similar in the rest of the countries (Alvarez *et al*., 2002).

FIGURE 1
Sensitivity of the Gini index to parameter "s" in Spain (1993-2000).
Source of data: ECHP.



Also, we have considered the OECD scale and the modified OECD one. The OECD scale gives a weight of 1 to the first adult, 0.7 to other persons aged 14 or over and 0.5 to each child aged less than 14 who are living in the household. On the other hand, the modified OECD scale gives a weight of 1 to the first adult, 0.5 to other persons aged 14 or over and 0.3 to each child aged less than 14. For each person, the "equivalised total net income" is calculated as its household total net income divided by equivalised household size.

3. POPULATION FUNCTIONS AND THE MEAUSUREMENT OF INCOME INEQUALITY

3.1 PREVIOUS RESULTS

Let L be the class of all non-negative random variables with positive finite expectation. For a random variable X in L with distribution function $F_X(x)$ we define its inverse distribution function $F_X^{-1}(x)$ by:

$$F_X^{-1}(p) = \inf\{x : F_X(x) \geq p\}.$$

The quantile function is given by:

$$X(p) = F_X^{-1}(p), \quad 0 \le p \le 1,$$

The quantile function represents the value of a variable for which p percent of the values of the distribution are smaller.

Thus, the Lorenz curve associated with X is defined by:

$$L_X(p) = \left[\int_0^p F_X^{-1}(y)dy \right] / \left[\int_0^1 F_Y^{-1}(y)dy \right], \quad 0 \le p \le 1.$$

Note that $\mu_X = \int_0^1 F_X^{-1}(y)dy$ is the expectation of the random variable X.

So, the quantile function can be obtained from the Lorenz curve:

$$X(p;\mu) = \mu L'_X(p), \quad 0 \le p \le 1,$$

The above definition suggests a method for obtaining quantile functions based on parametric Lorenz curves.

3.2 POPULATION FUNCTIONS

In this paper we use two particular quantile functions:

1) Beta quantile function:

$$X(p;a,b,\mu) = \frac{\mu p^{a-1}(1-p)^{b-1}}{B(a,b)}, \quad 0 \le p \le 1, \quad a \ge 1, \; 0 < b \le 1$$

where $B(.)$ represents the Euler beta function.

2) Gamma quantile function:

$$X(p;\alpha,\lambda,\mu)=\frac{\mu\lambda^{\alpha}p^{\lambda-1}(-\log p)^{\alpha-1}}{\Gamma(\alpha)},\quad 0\le p\le 1,\quad \alpha\le 1,\quad \lambda>1$$

where $\Gamma(.)$ represents the usual gamma function.

3.2.1 Properties of Beta and Gamma Quantile functions

The Beta quantile functions have been obtained from the following Lorenz curve:

$$L(p;a,b)=\int_0^p \frac{x^{a-1}(1-x)^{b-1}}{B(a,b)}dx,\quad a\ge b,\ 0<b\le 1.$$

This Lorenz curve is defined on $(0,\infty)$ and the Gini index is given by:

$$G(a,b)=\frac{a-b}{a+b}.$$

The k-th order moment for the variable X is given by:

$$E(X^k)=\mu^k\,\frac{B(k(a-1)+1,k(b-1)+1)}{B(a,b)^k},$$

and $E(X^k)<\infty \Leftrightarrow b\ge 1-1/k$.

The Gamma quantile functions have been obtained from the following Lorenz curve:

$$L(p;\alpha,\lambda)=\int_0^p \frac{\lambda^{\alpha}}{\Gamma(\alpha)}x^{\lambda-1}(-\log x)^{\alpha-1}dx,\ \lambda>1,\ \alpha>0.$$

The Gini index is given by:

$$G(\alpha,\lambda)=2\left(\frac{1}{1+\lambda^{-1}}\right)^{\alpha}-1.$$

The k-th order moment for the variable X is given by:

$$E(X^k)=\mu^k\,\frac{\lambda^{k\alpha}\Gamma(k(\alpha-1)+1)}{[k(\lambda-1)+1]^{k(\alpha-1)+1}\Gamma(\alpha)^k}.$$

3.3 Estimation of Beta Quantile Functions

For the estimation we begin with a set of n income data $(p_i, x(p_i)), \quad i = 1, 2, ..., n$ coming from the observed quantile functions. Replacing $(p_i, x(p_i))$ and taking logarithms, we obtain $(c = \log(\mu / B(a,b)))$:

$$\log x(p_i) = c + (a-1)\log p_i + (b-1)\log(1-p_i),$$

which is a linear model in the parameters. From this expression we can obtain the estimators of the parameters a, b y μ. An alternative robust method of estimation is given by Castillo, Hadi and Sarabia (1998).

3.4 Estimation of the Gamma Quantile Functions

By the same way, replacing and taking logarithms, we obtain:

$$\log x(p_i) = c + (\lambda - 1)\log p_i + (\alpha - 1)\log(-\log(p_i)), \quad 0 \leq p \leq 1,$$

$(c = \log(\mu\lambda^{\alpha} / \Gamma(\alpha)))$ which is again a lineal model in the parameters. From this expression we can obtain estimators of the parameters μ, λ y α.

3.5 Empirical Results

Results of the estimation of the quantile functions are presented in this section. Tables 1 and 2 include the estimators of both of the models together with the standard deviation of the parameters.

The empirical results reported in this study indicate that both models are very satisfactory in fitting data although gamma quantile functions are lightly better. Finally, from the corresponding estimators we have obtained the Gini indices for each year, each functional form and according to the different values of parameter "*s*".

TABLE 1

Fitted Beta Quantile Functions. Standard deviations in parentheses. Country: Spain. Source of data: ECHP.

Wave	*s*=0		*s*=0.25		*s*=0.5		*s*=0.75		*s*=1	
	a	*b*	*a*	*b*	*a*	*b*	*a*	*b*	*a*	*b*
1994	1.4727	0.6532	1.4106	0.6599	1.3726	0.661068	1.3714	0.6658	1.3985	0.6563
	(0.0176)	(0.0176)	(0.0137)	(0.0137)	(0.0092)	(0.0092)	(0.0087)	(0.0087)	(0.0076)	(0.0076)
1995	1.4587	0.6638	1.3892	0.6649	1.3571	0.6691	1.3633	0.6725	1.4000	0.6696
	(0.0193)	(0.0193)	(0.0160)	(0.0160)	(0.0121)	(0.0121)	(0.0094)	(0.0094)	(0.0081)	(0.0081)
1996	1.4478	0.6495	1.3905	0.6596	1.3603	0.6620	1.3703	0.6682	1.4037	0.6636
	(0.0208)	(0.0208)	(0.0167)	(0.0167)	(0.0103)	(0.0103)	(0.0121)	(0.0121)	(0.0098)	(0.0098)
1997	1,4619	0,6381	1,4075	0,6490	1,3829	0,6567	1,3923	0,6630	1,4294	0,6613
	(0,0190)	(0,0190)	(0,0171)	(0,0171)	(0,0112)	(0,0112)	(0,0115)	(0,0115)	(0,0111)	(0,0111)
1998	1,4464	0,6378	1,3924	0,6535	1,3670	0,6622	1,3746	0,6703	1,4125	0,6709
	(0,0243)	(0,0243)	(0,0188)	(0,0188)	(0,0112)	(0,0112)	(0,0108)	(0,0108)	(0,0088)	(0,0088)

TABLE 2

Fitted Gamma Quantile Functions. Standard deviations in parentheses. Country: Spain. Source of data: ECHP.

Wave	*s*=0		*s*=0.25		*s*=0.5		*s*=0.75		*s*=1	
	λ	α	λ	α	λ	α	λ	α	λ	α
1994	1.3514	0.6660	1.2922	0.6728	1.2556	0.6748	1.2571	0.6802	1.2813	0.6714
	(0.0196)	(0.0146)	(0.0149)	(0.0111)	(0.0108)	(0.0080)	(0.0128)	(0.0095)	(0.0126)	(0.0094)
1995	1.3409	0.6758	1.2723	0.6774	1.2427	0.6823	1.2512	0.6866	1.2873	0.6841
	(0.0219)	(0.0163)	(0.0179)	(0.0133)	(0.0144)	(0.0107)	(0.0134)	(0.0099)	(0.0128)	(0.0095)
1996	1.3248	0.6620	1.2718	0.6724	1.2437	0.6757	1.2573	0.6830	1.2893	0.6786
	(0.0237)	(0.0176)	(0.0191)	(0.0142)	(0.0124)	(0.0093)	(0.0177)	(0.0131)	(0.0154)	(0.0114)
1997	1,3352	0,6512	1,2852	0,6622	1,2644	0,6706	1,2774	0,6778	1,3144	0,6766
	(0,0211)	(0,0157)	(0,0195)	(0,0145)	(0,0135)	(0,0100)	(0,0168)	(0,0125)	(0,0172)	(0,0128)
1998	1,3191	0,6505	1,2712	0,6662	1,2502	0,6757	1,2619	0,6846	1,3004	0,6855
	(0,0281)	(0,0209)	(0,0214)	(0,0159)	(0,0130)	(0,0097)	(0,0154)	(0,0114)	(0,0139)	(0,0104)

4. INCOME INEQUALITY AND HEALTH: AN EMPIRICAL APPROACH BASED ON AGGREGATE DATA

Although there are many studies focused on the relationship between income and health using cross section country data suggesting that population health (measured by life expectancy or mortality) improves with average income but at a decreasing rate (*absolute income hypothesis*), new empirical investigations are focused on the *relative income* *hypothesis* (the health of individuals in a society also depends on the degree of income inequality in that society).

In this section, we empirically study if income distribution is significantly associated with life expectancy in the European Union. Firstly, we will focus on the traditional model proposed by Rodgers (1979):

$$L_k = \beta_0 + \beta_1 \frac{1}{y_k} + \beta_2 \frac{1}{y_k^2} + \beta_3 G_k + \varepsilon_k , \tag{2}$$

where L_k is life expectancy in country k, y_k is per capita income, y_k^2 is the square of per capita income, G_k is the Gini index and ε_k is an error term. Thus, life expectancy increases at a decreasing rate with income and tends to a maximum value. However, this relationship is asymptotic (that is, there is a maximum life expectancy beyond which increases in income have no effect). Thus, the relation between income and life expectancy is considered as non-linear.

Obviously, when we analyse the relationship between individual health and income using sums or averages individual level data, the aggregation problem may arise[3] (Deaton and Muelbauer, 1980).

In this way, Gravelle, Wildman and Sutton (2002) analyse whether aggregate studies can help us to identify the determinants of the health of individuals. These authors begin with a specific model of the determinants of individual mortality risk:

$$m_{jk} = \beta_0 + \beta_1 y_{jk} + \beta_2 y_{jk}^2 + \beta_3 R_{jk} + \beta_4 z_{jk} + e_{jk} , \tag{3}$$

where m_{jk} is the mortality risk of individual j in country k, y_{jk} is his/her income, R_{jk} is a variable which depends on the some characteristics of the distribution of income in country k

and intends to reflect the relative income hypothesis that an individual´s health depends on the income of others as well as his/her income, z_{jk} is another variable (or set of non income variables) affecting health and e_{jk} is an error term. So, taking expectations over the individuals in each country we obtain the following model:

$$m_k = \beta_0 + \beta_1 y_k + \beta_2 s_k + \beta_3 R_k + \beta_4 z_k + e_k \,, \tag{4}$$

where $m_k = E_j m_{jk}$ is population mortality in country *k*, $y_k = E_j y_{jk}$ is per capita income, $s_k = E_j y_{jk}^2$ is the average squared income, $R_k = E_j R_{jk}$, $z_k = E_j z_{jk}$ and $e_k = E_j e_{jk}$. So, our macro-model can therefore be specified as:

$$m_k = b_0 + b_1 y_k + b_2 y_k^2 + b_3 G_k + e_k \,, \tag{5}$$

where m_k is population mortality in country *k*, y_k is per capita income and G_k is some measure of income inequality such as Gini index.

5. RESULTS

This section provides results derived from the estimation using STATA 8.0. A variety of different model specifications were tried, using two different dependent variables (life expectancy at birth and infant mortality). Also the income variable was tried in a number of different specifications (including reciprocal, reciprocal quadratic and reciprocal logarithm). Finally, the income distribution variable used was the Gini index calculate considering different equivalence scales.

We have used panel techniques (see Jones, 2000; Ermisch, 2000; Green, 2003) and the fundamental advantage of this panel data set over a cross section is that it allows us great flexibility in modelling differences across European countries. The basic framework is a regression model of the form: $y_{it} = x_{it}\beta + \alpha_i + \varepsilon_{it}$. By this way, there are *K* regressors in x_{it}

(not including a constant term) and the heterogeneity (or individual effect) is α_i, which is taken to be constant over time, *t*, and specific to the individual cross-sectional unit, *i*. When we assume fixed effects, we suppose that differences across countries can be captured as differences in the constant term. In this case:

$$y_i = x_i\beta + i\alpha_i + \varepsilon_i, \tag{6}$$

and each α_i is considered as an unknown parameter to be estimated. This model can be extended including a time specific effect[4]:

$$y_{it} = x_{it}\beta + \alpha_i + \gamma_t + \varepsilon_{it}. \tag{7}$$

If we assume random effects, the unobserved individual heterogeneity is supposed to be uncorrelated with the included variables. The model is formulated as:

$$y_{it} = x_{it}\beta + (\alpha + u_i) + \varepsilon_{it}, \tag{8}$$

where there are K regressors including a constant and the single constant term is the mean of the unobserved heterogeneity.

Also, we have used Hausman's specification test for the random effects model. This specification, which was devised by Hausman (1978), is used to test for orthogonality of the random effects and the regressors[5].

Tables 3-6 show the results corresponding to several specifications. Also, we include Hausman tests which provides evidence of the existence of correlations between individual effects and the regressors. Finally, a Wald test is included to evaluate the joint significance of the variables.

TABLE 3: Results. Panel Data approach. Dependent variable: Life Expectancy (Male). Random Effects.

Variables	**Model 1**	**Model 2**	**Model 3**	**Model 4**	**Model 5**	**Model 6**	**Model 7**
(1/*GDPC per capita*) (Coefficient)	-0.20317360	-0.20210290	-0.20729580	-0.20470400	-0.20254700	-0.20127040	-0.20017160
Std. Error	(0.0556980)	(0.0557451)	(0.0562193)	(0.0560141)	(0.0558620)	(0.0558627)	(0.0559357)
T Statistic	-3.65	-3.63	-3.69	-3.65	-3.63	-3.60	-3.58
P-value	0.000	0.000	0.000	0.000	0.000	0.000	0.000
(1/*GDP per capita*)^2 (Coefficient)	0.00098860	0.00098190	0.00100720	0.00098910	0.00097640	0.00097070	0.00096800
Std. Error	(0.0004091)	(0.0004094)	(0.0004126)	(0.0004110)	(0.0004098)	(0.0004099)	(0.0004104)
T Statistic	2.42	2.40	2.44	2.41	2.38	2.37	2.36
P-value	0.016	0.016	0.015	0.016	0.017	0.018	0.018
Gini (modified OECD scale) (Coefficient)	-0.07549362						
Std. Error	(0.03665248)						
T Statistic	-2.06						
P-value	0.039						
Gini (OECD scale) (Coefficient)		-0.07344930					
Std. Error		(0.0378905)					
T Statistic		-1.94					
P-value		0.053					
Gini (s=0) (Coefficient)			-0.07900560				
Std. Error			(0.0382782)				
T Statistic			-2.06				
P-value			0.039				
Gini (s=0.25) (Coefficient)				-0.07378080			
Std. Error				(0.0367512)			
T Statistic				-2.01			
P-value				0.045			
Gini (s=0.5) (Coefficient)					-0.07125890		
Std. Error					(0.0364040)		
T Statistic					-1.96		
P-value					0.050		
Gini (s=0.75) (Coefficient)						-0.06952660	
Std. Error						(0.0377155)	
T Statistic						-1.84	
P-value						0.065	
Gini (s=1) (Coefficient)							-0.07016460
Std. Error							(0.0407982)
T Statistic							-1.72
P-value							0.085
R-square	0.4937	0.4898	0.4921	0.4921	0.4909	0.4869	0.4820
Wald Statistic and Prob(Wald)	75.33 (0.0000)	74.88 (0.0000)	73.18 (0.0000)	73.86 (0.0000)	74.41 (0.0000)	74.21 (0.0000)	73.74 (0.0000)
Hausman Statistic and Prob(Hausman)	4.26 (0.2347)	3.48 (0.3233)	4.21 (0.2396)	4.58 (0.2052)	4.25 (0.2354)	3.23 (0.3578)	1.92 (0.5890)

Source: Authors´ calculations from ECHP, Eurostat and OECD Health Data.

TABLE 4: Results. Panel Data approach. Dependent variable: Life Expectancy (Male). Fixed Effects.

Variables	**Model 1**	**Model 2**	**Model 3**	**Model 4**	**Model 5**	**Model 6**	**Model 7**
(1/*GDPC per capita*) (Coefficient)	-0.19777570	-0.19672970	-0.20073950	-0.19852400	-0.19655150	-0.19538070	-0.19419900
Std. Error	(0.0546773)	(0.0548948)	(0.0547645)	(0.0547513)	(0.0548195)	(0.0550576)	(0.0553490)
T Statistic	-3.62	-3.58	-3.67	-3.63	-3.59	-3.55	-3.51
P-value	0.000	0.001	0.000	0.000	0.001	0.001	0.001
$(1/GDP\ per\ capita)^2$ (Coefficient)	0.00088200	0.00088010	0.00087390	0.0006650	0.00086290	0.00086410	0.00086550
Std. Error	(0.0004034)	(0.0004051)	(0.0004036)	(0.0004035)	(0.0004040)	(0.0004059)	(0.0004082)
T Statistic	2.19	2.17	2.17	2.15	2.14	2.13	2.12
P-value	0.031	0.032	0.033	0.034	0.035	0.036	0.037
Gini (modified OECD scale) (Coefficient)	-0.09650590						
Std. Error	(0.0380399)						
T Statistic	-2.54						
P-value	0.013						
Gini (OECD scale) (Coefficient)		-0.09391380					
Std. Error		(0.0394465)					
T Statistic		-2.38					
P-value		0.019					
Gini (s=0) (Coefficient)			-0.09846120				
Std. Error			(0.0394349)				
T Statistic			-2.50				
P-value			0.014				
Gini (s=0.25) (Coefficient)				-0.09464400			
Std. Error				(0.0380219)			
T Statistic				-2.49			
P-value				0.015			
Gini (s=0.5) (Coefficient)					-0.09192260		
Std. Error					(0.0377578)		
T Statistic					-2.43		
P-value					0.017		
Gini (s=0.75) (Coefficient)						-0.08852050	
Std. Error						(0.0391693)	
T Statistic						-2.26	
P-value						0.026	
Gini (s=1) (Coefficient)							-0.08628360
Std. Error							(0.0424235)
T Statistic							-2.03
P-value							0.045
R-square	0.4963	0.4922	0.4952	0.4950	0.4936	0.4892	0.4839
F Statistic and Prob(F)	29.23 (0.0000)	28.76 (0.0000)	29.11 (0.0000)	29.08 (0.0000)	28.92 (0.0000)	28.41 (0.0000)	27.81 (0.0000)

Source: Authors´ calculations from ECHP, Eurostat and OECD Health Data.

TABLE 5: Results. Panel Data approach. Dependent variable: Child Mortality. Random Effects.

Variables	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7
(1/*GDPC per capita*) (Coefficient)	-0.82907870	-0.77449100	-0.81999190	-0.76934960	-0.72447730	-0.80325370	-0.74520510
Std. Error	(0.2851968)	(0.2826027)	(0.3912987)	(0.3800448)	(0.3717302)	(0.2813448)	(0.2758827)
T Statistic	-2.91	-2.74	-2.10	-2.02	-1.95	-2.86	-2.70
P-value	0.004	0.006	0.036	0.043	0.051	0.004	0.007
(1/*GDP per capita*)^2 (Coefficient)	0.01938350	0.01824580	0.04465918	0.04117910	0.03818180	0.01888520	0.01774690
Std. Error	(0.0080650)	(0.0080181)	(0.0179478)	(0.0174784)	(0.0171333)	(0.0079743)	(0.0078515)
T Statistic	2.40	2.28	2.49	2.36	2.23	2.37	2.26
P-value	0.016	0.023	0.013	0.018	0.026	0.018	0.024
Gini (modified OECD scale) (Coefficient)	0.05717900						
Std. Error	(0.0324772)						
T Statistic	1.76						
P-value	0.078						
Gini (OECD scale) (Coefficient)		0.06896860					
Std. Error		(0.0325499)					
T Statistic		2.12					
P-value		0.034					
Gini (s=0) (Coefficient)			0.06499690				
Std. Error			(0.04186315)				
T Statistic			1.55				
P-value			0.012				
Gini (s=0.25) (Coefficient)				0.07900720			
Std. Error				(0.0396217)			
T Statistic				1.99			
P-value				0.046			
Gini (s=0.5) (Coefficient)					0.09287610		
Std. Error					(0.0383154)		
T Statistic					2.42		
P-value					0.015		
Gini (s=0.75) (Coefficient)						0.06757200	
Std. Error						(0.0330966)	
T Statistic						2.04	
P-value						0.041	
Gini (s=1) (Coefficient)							0.09036170
Std. Error							(0.0347555)
T Statistic							2.60
P-value							0.009
R-square	0.4345	0.4571	0.4021	0.4362	0.4677	0.4519	0.4882
Wald Statistic and Prob(Wald)	48.82 (0.0000)	50.31 (0.0000)	20.88 (0.0001)	23.30 (0.0000)	25.96 (0.0000)	50.18 (0.0000)	53.58 (0.0000)
Hausman Statistic and Prob(Hausman)	11.44 (0.0096)	10.54 (0.0145)	10.83 (0.0127)	11.68 (0.0086)	11.55 (0.0091)	10.61 (0.0140)	9.16 (0.0272)

Source: Authors´ calculations from ECHP, Eurostat and OECD Health Data.

TABLE 6: Results. Panel Data approach. Dependent variable: Child Mortality. Fixed Effects.

Variables	**Model 1**	**Model 2**	**Model 3**	**Model 4**	**Model 5**	**Model 6**	**Model 7**
(1/*GDPC*) (Coefficient)	-1.76529600	-1.76174700	-1.39351100	-1.3824800	-1.79354700	-1.77732440	-1.76391100
Std. Error	(0.6385843)	(0.5355680)	(0.3100276)	(0.3102315)	(0.6372129)	(0.6332302)	(0.6264760)
T Statistic	-2.76	-2.77	-4.49	-4.46	-2.81	-2.80	-2.82
P-value	0.007	0.007	0.000	0.000	0.006	0.007	0.006
$(1/GDPC)^2$ (Coefficient)	0.10276210	0.10205730	0.03272960	0.03246990	0.10440600	0.10270680	0.10090480
Std. Error	(0.0312556)	(0.0311413)	(0.0085292)	(0.0085347)	(0.0311755)	(0.0310166)	(0.0307397)
T Statistic	3.29	3.28	3.84	3.80	3.35	3.31	3.28
P-value	0.002	0.002	0.000	0.000	0.001	0.001	0.002
Gini (OCDEco) (Coefficient)	0.09743001						
Std. Error	(0.0372649)						
T Statistic	1.54						
P-value	0.128						
Gini (OCDE) (Coefficient)		0.08691080					
Std. Error		(0.0506144)					
T Statistic		1.72					
P-value		0.090					
Gini (s=0) (Coefficient)			0.05141509				
Std. Error			(0.0447358)				
T Statistic			1.15				
P-value			0.255				
Gini (s=0.25) (Coefficient)				0.05151843			
Std. Error				(0.04365859)			
T Statistic				1.18			
P-value				0.242			
Gini (s=0.5) (Coefficient)					0.098587980		
Std. Error					(0.03704866)		
T Statistic					1.52		
P-value					0.134		
Gini (s=0.75) (Coefficient)						0.09134180	
Std. Error						(0.0504190)	
T Statistic						1.81	
P-value						0.074	
Gini (s=1) (Coefficient)							0.11433260
Std. Error							(0.0522015)
T Statistic							2.19
P-value							0.032
R-square	0.3824	0.3923	0.3880	0.3955	0.3787	0.3937	0.4130
F Statistic and Prob(F)	6.03 (0.0010)	6.26 (0.0000)	16.51 (0.0000)	16.55 (0.0000)	6.00 (0.0011)	6.40 (0.0000)	7.01 (0.0003)

Source: Authors´ calculations from ECHP, Eurostat and OECD Health Data.

Tables 3 and 4 give the results with Life Expectancy (Male) as dependent variable using the reciprocal of GDP per capita and its square, together with the Gini coefficient as independent variables. All three variables are significant and the non-logarithmic formulation is preferable. The level of explanation, as measured by R^2, is acceptable. Also, signs of variables are those to be expected and their statistical significance is accepted. Other results with child mortality as dependent variable are given in Tables 5 and 6. R^2 is lower than for life expectancy but the results are similar.

6. CONCLUSIONS

This paper provides new evidence on the relationship between income inequality and health in the European Union. The results give strong support to the influence of income inequality on health indicators using aggregate data. This is a very important conclusion which holds across a variety of specifications and with each of the two dependent variables considered. We have carried out this approach to the case of the European countries over the period 1993-2000 using new data based on the ECHP and different equivalence scales. The most important result is the influence of the income distribution variable and the sign of the income distribution coefficients were always as expected: Greater inequality is associated with higher mortality. On the other hand, the results for greater life expectancy are associated with lower inequality. Obviously, environmental and social variables (social capital) are important in terms of health but at least, the relationship between income and health must be taken into account in order to make adequate health care policies.

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[1]Austria joined the project since 1995 and Finland in 1996. Also, similar data is available for Sweden from 1997 onwards. However, the original ECHP surveys were stopped in 1997 in Germany, Luxembourg and the United Kingdom where national surveys were used.

[2] This is obtained by dividing the national currency amounts by purchasing power parities provided by EUROSTAT taking into account that most income information refers to the previous year.

[3] Waldmann (1992) mitigated the aggregation problem by including additional information on income levels of the non-rich as well as income share of the rich.

[4] This model is obtained including T-1 dummy variables (one of the time effects is dropped to avoid perfect collinearity).

[5] Hausman's essential result is that the covariance of an efficient estimator with its difference from an inefficient estimator is zero.