UNDERSTANDING THE EFFECT OF EDUCATION ON HEALTH ACROSS EUROPEAN COUNTRIES[1]

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ABSTRACT

En este artículo se explora la relación entre educación y salud para once países de la Unión Europea. Se estima para cada país una función de producción de salud siguiendo la teoría del capital humano de Grossman en la que la educación es uno de los inputs más relevantes. Para ello se consideran las ocho olas del Panel de Hogares de la Unión Europea (1994-2001). El indicador de salud utilizado es un indicador de autovaloración de salud que toma cinco posibles valores. La estrategia empírica seguida es la de los modelos probit ordenados generalizados con efectos aleatorios. El resultado fundamental del trabajo es que para todos los países la educación mejora la salud aunque con distinta intensidad. También se aprecian rendimientos decrecientes de la educación sobre la salud.

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1. INTRODUCCIÓN

This study is aimed at analysing the relations between health and education in different countries of the European Union. Empirical evidence on the relation between education and health is quite rich, although it does not equally cover all countries in the European Union. Literature for the US is quite spread whereas pieces of work either on Europe or on different European countries are rather scarce. Exceptions are those based in Denmark (Wagstaff, 1986, 1993), East Germany (Erbsland et al, 1995 and Pohlmeier and Ulrich, 1995), Great Britain (Contoyannis et al, 2004), The Netherlands (Hartog and Oosterbeek, 1998), Spain (Albert and Davia, 2004) and Sweden (Gerdtham and Johannesson, 1999 and Bolin et al, 2002). Comparative analyses are even scarcer, and so far they have been hindered by the lack of the suitable comparable information. We try to enrich this strand of the literature by contributing with results for the link between health and education in eleven European Union countries.

We will deploy the European Community Household Panel (ECHP) from 1994 to 2001. This data set gathers very interesting information about health variables, education and labour market issues amongst other aspects, such as income. The ECHP offers a possibility to compare countries, although it is not free of shortcomings. They arise from differences between the national questionnaires as regards health questions, which are more pronounced than differences in other parts of the questionnaire. Moreover, the questions about health have changed along the observation period, particularly from the fifth interview onwards. Since our contribution is to obtain a health production function for as many countries (and waves) as possible, we have chosen eleven of the European Union countries where there are eight waves of available information. This strategy has implied renouncing to several explanatory variables in the estimation of the health production function, although we think this has been worth doing for two reasons: on the one hand, our analysis enables the comparison of the effect of education level on health in eleven countries; on the other hand we may use panel data methodologies, namely, a random effects ordered probit. With this technique we may take into account the potential impact unobserved heterogeneity, which is very relevant in the study of health determinants and health outcomes. We have computed a log-likelihood test to contrast the increase in the goodness of fit of the model when including this particular nuance. Results of the test showed that, with no exception, the inclusion of individual random effects significantly contribute to the goodness of fit of the models, so that trust more the random effect specification.

The contents of the article are as follows: Section 2 presents the theory framwork; Section 3 presents the empirical model; Section 4 summarises the main results; and finally, section 5 concludes.

2. THE EFFECT OF EDUCATION ON HEALTH

Health economists have tried to understand the positive link between education and health and empirical analysis has confirmed it once and again exploring three hypotheses: productive efficiency, allocative efficiency and the time preference hypotheses. The productive efficiency and allocative efficiency hypothesis predict a causal relation between education attainment and health (Grossman 1972). In the former hypothesis, this link is due to the fact that educated agents will be more efficient in the use of health care services and, therefore, in the production of health. One of the main problems to contrast this hypothesis is that both education and income are relevant inputs in a health production function, but income does depend as well on education. Therefore income is an endogenous variable in a single equation health production function. In order to tackle this endogeneity, two approaches are available: instrumental variables and simultaneous equations. For instrumental variables Grossman (2004) displays a survey of recent contributions to this type of literature and for a simultaneous equation approach, see Lee (1982).

In the second approach (allocative efficiency hypothesis) education is seen as a driving force (similar to a catalyst) in health related decisions. Educated individuals are more aware of the consequences of unhealthy habits and will tend to invest more time and resources on health care. Therefore, we might expect a direct effect of education on health. One way to test this hypothesis would consist in observing whether the education coefficient tends to lose explanatory power as we include more and more inputs in the health production function (Rosenzweig and Schultz, 1989).

In the third approach, the time preference hypothesis, those agents with a low time discount rate who prefer future consumption to present consumption tend to invest more resources on human capital (on both education and health), so that the positive link between both variables is not causal (Fuch, 1982 and Farrell and Fuchs, 1982). Unfortunately it is difficult to contrast this hypothesis, since time preference is not the only omitted variable we may have in a health production function. Contrasting this hypothesis is very difficult since time preference not easy to measure. Different authors have made use of instrumental variables as an empirical strategy to control for time preference; they have tried to find a valid instrument, i.e., a variable that is linked to health and not to education. Needless to say, this is a particularly challenging endeavour (Grossman, 2004).

No matter the chosen technique, most of the empirical pieces of work on this area conclude that formal completed schooling is the most important correlate of good health. This finding emerges regardless both the way of measuring health levels and the units of observation (individuals or groups). Another interesting result suggests that schooling is a more important correlate of health than occupation or income. As the allocative efficiency hypothesis stresses, schooling is a causal determinant of occupation and income, so that the “gross” effect of schooling on health may partially reflect its impact on the socioeconomic status.

3. EMPIRICAL MODEL

We will start by developing a health production function on wage-earners; this model should be interpreted as a reduced form specification of the production function of health since we are not able to include neither inputs such as health care nor variables regarding healthy habits due to problems with the questionnaire. In this model, variable H^*_{it} is a self-assessed health status representing the health stock of individual *i* at time *t*. This variable is a latent unobservable outcome, but we can observe in the data an indicator of the category in which the latent outcome falls (H_{it}); it is an ordered discrete variable taking five values, the actual values taken on by the dependent variable are irrelevant except that larger values are assumed to correspond to "higher" outcomes (health). The observed mechanism can be described in the following way:

$$H_{it} = n \;\; if \;\; \pi_{n-1} < H^*_{it} \leq \pi_n \, , \; n=1,....,m \qquad (1)$$

where π's are called thresholds or cutpoints. The extreme categories 1 and m are defined by open-end intervals with $\pi_0 = -\infty$, $\pi_m = \infty$, and $\pi_n \leq \pi_{n+1}$.

The probability of observing the self assessed health status n for agent i in time *t* (H_{it}) is: $P_{itn} = P(H_{it} = n) = \S\,(\bullet)$, where $\S\,(\bullet)$ is the standard normal distribution function.

The reduced form model of latent variable can be express by lineal regression structure:

$$H^*_{it} = \beta_0 + \beta_1 Y_i + \beta_2 X_{it} + \beta_4 D_t + u_i + s_{it} \qquad (2)$$

where Y_i is observable time invariant factors (the education level and gender) and X_{it} is the observable time varying factors (the wage, hours of work, age and living alone). We included eight dummy variables (D_t), one for each wave, in order to detect institutional (among other types) changes along time. This derives in a two-way regression model where we may control both dimensions of the problem: time (differences along time within individuals) and "space" (differences across individuals in a given moment of time). Finally, u_i is an individual specific error term; it is assumed to be a random component which will not change over time. s_{it} is a time and individual specific error term and it is assumed to be exogenous, normally distributed and uncorrelated across individuals and along time and with u_i. Finally, β's are parameters to be estimated.

Our precise first empirical strategy consists on an ordered probit with control for random effects. We must here pay attention to a very important nuance: ordered dependent variable models are based on one very relevant assumption, the so called "proportional odds assumption" or the "parallel regression assumption" (Long and Freese, 2006). It consists on assuming that the relationship between each pair of outcome groups is the same. In other words, ordered probit (or logistic) regression assumes that the coefficients that describe the relationship between categories 1 and 2 is the same that the one that describes relationship between categories 4 and 5. If this were true, just one set of coefficients would be enough to describe the fitting of the dependent variable. We have tested the proportional odds assumption, via a likelihood ratio test. The null hypothesis of this test is that there is no difference in the coefficients between models, and we widely rejected it in all countries. We are interested in random effects since (unlike fixed effects) they allow us to identify parameters for time-invariant dependent variables. This is precisely the case of education, our most relevant explanatory variable.

This means that a standard ordered probit model does not properly describe the link between different educational levels and different health statuses, and we need instead a generalized ordered probit, both in a pooled version and in a random effects version. The generalized model relaxes the parallel regression assumption of standard ordered probit models and its random effects counterpart. In these models all the parameters are outcome-specific. This is very interesting for our problem, since we will be able to observe how education contributes both to prevent poor health situations and to access to the highest values of the ranking, that is, we have obtained a different set of coefficients for each outcome. We have led all β_j coefficients free to vary across outcomes. The likelihood contribution for each cross-sectional unit in the above model is approximated using a Gaus-Hermite quadrature (Boes and Wikelman, 2006). The ordered probit model is estimated using the user-provided commands for generalised pooled order probit and generalised random effects ordered probit estimators available in STATA.

4. RESULTS

Table 1 displays the results for education attainment variables of our models; we will not provide with the model coefficients but with the estimated marginal probability effects: we are interested on how much the probability of each outcome in the health status distribution responds to a change from 0 to 1 in dummies representing education attainment.

Greene (2003; p 740) asserts that marginal effects for are not appropriate for evaluating the effect of a dummy variable. He recommends instead comparing the probabilities that result when the variable takes its two different values (with each other and with the values that occur with the other variables held at their sample means). Long (1997; p 135) also stressed that measures of discrete change are much more informative than marginal effects. We therefore display results in two different locations: in the text we display marginal effects of binary variables (namely, average probabilities of all the outcomes of our dependent variable) for educational attainment indicators, which are our main explanatory variables. A complete set of the coefficients for the random effects generalized ordered probit is available from the authors.

For computational reasons we have had to reduce the initially five values in the dependent variable to only four. We have merged values 1 and 2 since they a very small number of interviewees reported them and in some models the likelihood function just did not converge. For the sake of consistency, we have estimated as many models as possible with a five value dependent variable as well as the shown four value dependent variable's, and results do not change: categories 3, 4 and 5 remain almost exactly the same regardless the aggregation of values in the dependent variable. Categories 1 and 2 registered always negative or non significant coefficients, so that the reported marginal effects are not the blurred result of different trends, but the summary of a similar effect.

The interpretation of marginal probability effects p_{ei} is the average probability of being in category "i" of the health variable of individuals with level of education "e". For instance, Table 1 shows that in Germany, the probability of reporting a bad or very bad health status amongst tertiary education graduates is 0.092 (9.2 per cent), whereas the probability of reporting a good health status for the same group is 0.502 (50 per cent). We have computed as well the contribution to the probability of upper secondary (ISCED-3) versus less than upper secondary (ISCED 0-2) and tertiary (ISCED 5-7). Finally, in order to detect decreasing marginal returns to education we report as well the difference in the probability of being in the four states of health between those interviewees with tertiary versus secondary. For example, we may interpret in Table 1 that an upper secondary education graduate is 0.061 (6.1 percentage points) (*row a*) less likely to report being in a bad/very bad health status that somebody with less than that education. Accordingly, in Germany tertiary university graduates are 0.075 (percentage points) less likely to report a bad health status than those with less than upper secondary (*row b*). As a result, tertiary education graduates are 0.014 (1.4 percentage points) more likely than upper education graduates of reporting a bad or very bad health status (*row c*).

TABLE 1
MARGINAL EFFECTS OF BINARY DEPENDENT EDUCATION VARIABLES ON HEALTH. GENERALISED RANDOM EFFECTS ORDERED PROBIT (*)

	D	DK	NL	B	F	UK	IRE	I	EL	E	P
Bad and very bad (1&2)											
MPE for ISCED 5-7	0.092	0.012	0.012	0.012	0.021	0.056	0.004	0.018	0.005	0.01	0.018
MPE for ISCED 3	0.106	0.014	0.018	0.019	0.028	0.059	0.006	0.024	0.006	0.016	0.022
MPE for ISCED 0-2	0.167	0.029	0.023	0.026	0.048	0.064	0.01	0.044	0.02	0.044	0.087
a) MPE_{ISCED3}-$MPE_{ISCED0-2}$	*-0.061*	*-0.015*	*-0.006*	*-0.007*	*-0.019*	*-0.004*	*-0.004*	*-0.02*	*-0.014*	*-0.028*	*-0.065*
b) $MPE_{ISCED5-6}$-$MPE_{ISCED0-2}$	*-0.075*	*-0.017*	*-0.012*	*-0.014*	*-0.027*	*-0.007*	*-0.006*	*-0.026*	*-0.015*	*-0.034*	*-0.069*
c) $MPE_{ISCED5-6}$-MPE_{ISCED3}	*-0.014*	*-0.002*	*-0.006*	*-0.007*	*-0.007*	*-0.003*	*-0.002*	*-0.006*	*-0.002*	*-0.006*	*-0.004*
Fair (3)											
MPE for ISCED 5-7	0.319	0.087	0.13	0.114	0.255	0.182	0.063	0.215	0.037	0.115	0.21
MPE for ISCED 3	0.321	0.119	0.153	0.155	0.274	0.185	0.075	0.23	0.04	0.135	0.229
MPE for ISCED 0-2	0.326	0.167	0.167	0.197	0.323	0.207	0.112	0.296	0.11	0.196	0.351
a) MPE_{ISCED3}-$MPE_{ISCED0-2}$	*-0.005*	*-0.047*	*-0.014*	*-0.042*	*-0.048*	*-0.022*	*-0.037*	*-0.066*	*-0.07*	*-0.061*	*-0.121*
b) $MPE_{ISCED5-6}$-$MPE_{ISCED0-2}$	*-0.006*	*-0.079*	*-0.036*	*-0.083*	*-0.067*	*-0.024*	*-0.049*	*-0.081*	*-0.073*	*-0.082*	*-0.141*
c) $MPE_{ISCED5-6}$-MPE_{ISCED3}	*-0.001*	*-0.032*	*-0.022*	*-0.04*	*-0.019*	*-0.002*	*-0.012*	*-0.015*	*-0.003*	*-0.021*	*-0.02*
Good (4)											
MPE for ISCED 5-7	0.502	0.34	0.604	0.572	0.554	0.484	0.326	0.569	0.235	0.625	0.705
MPE for ISCED 3	0.478	0.342	0.632	0.578	0.545	0.504	0.341	0.558	0.22	0.614	0.686
MPE for ISCED 0-2	0.413	0.354	0.605	0.553	0.507	0.5	0.408	0.494	0.284	0.583	0.528
a) MPE_{ISCED3}-$MPE_{ISCED0-2}$	*0.065*	*-0.012*	*0.027*	*0.025*	*0.038*	*0.003*	*-0.067*	*0.064*	*-0.064*	*0.031*	*0.158*
b) $MPE_{ISCED5-6}$-$MPE_{ISCED0-2}$	*0.089*	*-0.014*	*-0.001*	*0.019*	*0.046*	*-0.017*	*-0.082*	*0.075*	*-0.05*	*0.042*	*0.177*
c) $MPE_{ISCED5-6}$-MPE_{ISCED3}	*0.023*	*-0.002*	*-0.028*	*-0.006*	*0.008*	*-0.02*	*-0.016*	*0.011*	*0.014*	*0.011*	*0.019*
Very good (5)											
MPE for ISCED 5-7	0.087	0.561	0.254	0.302	0.17	0.277	0.608	0.198	0.723	0.251	0.067
MPE for ISCED 3	0.094	0.525	0.198	0.248	0.153	0.252	0.577	0.188	0.733	0.235	0.063
MPE for ISCED 0-2	0.094	0.451	0.205	0.225	0.123	0.229	0.47	0.166	0.586	0.176	0.035
a) MPE_{ISCED3}-$MPE_{ISCED0-2}$	*0*	*0.074*	*-0.007*	*0.024*	*0.03*	*0.023*	*0.107*	*0.022*	*0.148*	*0.058*	*0.028*
b) $MPE_{ISCED5-6}$-$MPE_{ISCED0-2}$	*-0.008*	*0.11*	*0.049*	*0.077*	*0.048*	*0.048*	*0.138*	*0.032*	*0.138*	*0.074*	*0.033*
c) $MPE_{ISCED5-6}$-MPE_{ISCED3}	*-0.008*	*0.036*	*0.056*	*0.053*	*0.018*	*0.025*	*0.03*	*0.01*	*-0.01*	*0.016*	*0.004*

(*) Other explanatory variables were gross hourly wage, hours of work, gender, age and year dummies.
Source: ECHP 1994-2001; Eurostat.

The probabilities of being in different health statuses vary considerably across countries: the most frequent answer is “good” in all countries except in Denmark, Ireland and Greece, where more than 50% of respondents report been in a “very good” health status. At the same time, “very good” is extraordinarily infrequent in Denmark and Portugal compared to other countries. It is difficult to rank countries according to the estimated health probabilities, but a ranking would have Greece, Ireland and Denmark in the top three places, and Germany and Portugal amongst the ones at the bottom.

Our aim was not to compute health probabilities themselves but differences in health across education attainment levels. The first general remarkable trend is that education contributes to reduce the probability of reporting both bad or very bad (values 1 and 2) and fair (value 3) states of health. The intensity of the reduction varies across countries. If we look at the reduction of the risk of feeling bad or very bad, it is strongest in Germany and Portugal, and mildest in Ireland and UK. If we instead focus on the reduction of the risk of feeling just in a “fair” health status, we see the highest reaction to education in Portugal. Something we can appreciate in almost all cases is that education attainment registers diminishing returns in its ability to reduce health problems: in all countries the reduction in the probability to reduce poor health status is stronger for tertiary education graduates than for upper secondary education graduates, but the relative decrease in the risk is stronger from lower secondary and less to upper secondary that from upper secondary to tertiary. Something similar, but in the opposite direction, may be appreciated in the best health outcomes, as we will see later.

The trend as regards the influence on feeling just “good” (value 4) is a bit more blurred: here we may distinguish between three types of countries: those where both upper secondary (*row a*) and tertiary education (*row b*) contribute to increase the probability of reporting a good health status (Germany, Belgium, France, Italy, Spain and Portugal), tertiary education (*row b*) contributes to reduce the probability of reporting a good health status (Denmark, Ireland and Greece) and those where secondary education (*row a*) increases the probability of feeling “good” but tertiary education decreases and, instead, drives interviewees to feeling “very good” (The Netherlands and UK). For example, in Table 1, in Germany upper secondary contributes 6.5 percentage points to increase the likelihood of feeling well versus lower secondary and less (*row a*), tertiary also contributes positively to this likelihood, with a 8.9 percentage points increase (*row b*). But the trend is different in the Denmark, where any of the levels of education hardly differ in the likelihood of feeling well (1.2 and 1.4 percentage points respectively compared to lower secondary) since they have a stronger influence on the likelihood of feeling very well.

Finally, in all countries except the Netherlands and Germany secondary education contributes to increase the probability to feel in a “very good” health status. And in all countries except in Germany tertiary education contributes to increase the probability of reporting a “very good” health status.

The abovementioned diminishing returns effect is present in almost all countries in the case of the contribution of education reporting good health statuses. In most cases, tertiary education contributes to increase the likelihood of feeling very well more than secondary education, but the increase in this probability is lower when comparing tertiary and upper secondary than upper secondary compared to lower secondary (at most). For instance, in Table 1 it may be seen that in Denmark upper secondary education increases in 7.4 percentage points the probability of reporting very good health compared to lower levels. At the same time, the increase due to tertiary education is even stronger, 11 percentage points. But the increase between upper secondary and tertiary only means 3.6 percentage points. A similar trend may be seen in France, Ireland, Italy, Greece, Spain and Portugal. In some other cases the impact of tertiary education is so strong that returns to tertiary education compared to upper secondary are even higher than returns to upper secondary compared to lower secondary: Belgium, UK and, in a different way, The Netherlands. This result is consistent with our human capital theoretical framework: being education an input or an efficiency factor in the health production function, as in any other human capital approach, further investments may contribute to higher returns, but at a decreasing rate.

5. CONCLUSIONS

The analysis performed in this paper has shown that the impact of education on health is positive even when we control for other inputs in the production function and take unobserved heterogeneity into account, and it remains positive in all countries. This result contributes to understand education as a very important input and efficiency factor in the health production function. The fact that we also observe diminishing returns in the reduction of poor health risks and increase of very good health statuses also contributes to our understanding of the nature of education and health as both human capital and health as a self-provided good, as Grossman's human capital approach postulates.

This result emphasises the fact that investment in health care is not the only way to invest on future health, since the determinants of health are not only related to the health system. Inasmuch health in developed countries is determined by lifestyles and healthy habits, healthcare systems are not the only responsible for health in developed countries. Citizens may influence their health status via the occupational choices and lifestyles they adopt, and higher qualified individuals are proved to be persistently better in the production of health. That means that more and more responsibilities will correspond to the education system in pursue of more welfare since, as our results show, education and health are very closely linked to each other.

We have as well contributed to the literature in showing how diverse European countries are regarding the impact of education on health. This means that policies meant to increase health are not necessarily to be similar in all these countries, since the health production pattern is quite nation-specific. Therefore national specificities need to be taken into account when designing education and health fostering policies.

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