

DIFFERENT CHANNELS OF IMPACT OF EDUCATION ON POVERTY: AN ANALYSIS FOR COLOMBIA

Blanca Zuluaga¹

...if we take into account a good life, then, as I have already said, education and virtue have superior claims. "Politics". Aristotle.

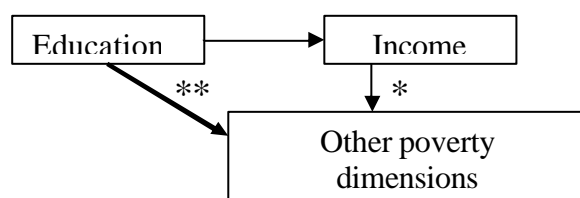
1. Introduction

It is common in the human capital literature to define returns to education exclusively in terms of the extra income it generates for individuals (Mincer (1974)), Hungerford and Solon (1987), Layard and Psacharopoulos (1974)). However, the influence of education on poverty is not limited to the pecuniary impact through income and wages. There are relevant non-pecuniary effects, reflected in variations of each of the different poverty dimensions, e.g. health, nutrition, housing, etc.

There exists a vast amount of contributions in the literature of multidimensional poverty, according to which poverty should not be analysed exclusively as a problem of lack of income (Sen (1985)). Indeed, the most recent literature on measurement of poverty has been oriented to provide an appropriate methodology for the estimation of aggregate multidimensional indices (Atkinson and Bourguignon (1982), Bourguignon and Chakravarty (1999), Tsui (1994, 2002)). Following this line of research, a proper analysis of the impact of education on poverty should consider not only its income dimension: other channels of impact on different poverty dimensions are also relevant.

As Sen has often emphasised, being educated helps individuals in the conversion of money and resources into functionings² (arrow* in figure 1 below). In addition, education influences the behaviour of the individuals, their aptitudes, attitudes and opportunities. This influence is reflected in a greater capacity to overcome poverty conditions, beyond the influence on income (arrow** in figure 1).

Figure 1.



¹ Centre for Economic Studies - CES, Katholieke Universiteit Leuven and Universidad Icesi Colombia. I am grateful to the National Department of Statistics of Colombia (DANE) for providing the database. Comments from my supervisor Erik Schokkaert, from professors Geert Dhaene and Paul de Grauwe have been very helpful.

² The concept of functionings comes from the theoretical framework of the "capability approach" and refers to actual achievements attained by an individual.

This paper will focus on analysing both the pecuniary and non-pecuniary effects of education on poverty. Specifically, we will estimate non-pecuniary impact by controlling for income effects. Although there are important channels of impact of education regarded as public goods - e.g. criminality reduction, social cohesion – (Haveman and Wolfe (1984)), we will consider here only private returns. Specifically, we will focus on those non-pecuniary private returns affecting different dimensions of poverty (basic needs).

There are two main contributions of this paper: first, the pecuniary analysis employs the recently developed technique of quantile regression (Koenker and Bassett (1978), Koenker and Hallock (2001)). This methodology is very helpful especially when one is interested in the lowest or highest extremes of the distribution function of the dependent variable. In fact, there is no reason to believe that the estimates of the effects of education on the income of households or individuals do not vary between the lowest and the upper tail of the income distribution. By using the traditional Least Square estimation, we would obtain only the effect of education on the conditional mean of the response variable. In contrast, quantile regression offers coefficient estimations for any conditional quantile.

The second contribution derives from our purpose to highlight the non-pecuniary returns to education: resources invested in education bring future returns to individuals, not only reflected in monetary earnings, but also in higher levels of satisfaction of basic needs.

This paper is organised as follows. The second section presents a short review of the theory on educational returns. There, we briefly expose the main ideas of the human capital theory; In addition, we point out the different channels of impact of education, emphasising those related to poverty.

In the third section, we briefly explain the methodology of quantile regression and present the estimations of pecuniary educational returns. The results of the instrumental variable quantile regression confirm the heterogeneity of the effect of education across quantiles of the conditional household-income distribution.

The fourth section focuses on the non-pecuniary effects. The estimates reflect the relevance of these non-pecuniary effects, and confirm that an analysis based only on monetary outcomes is incomplete. In the fifth section we perform a simulation based on the impact of an educational improvement whereby everyone manages to reach 11 years of education as a minimum. By calculating an Index of Poverty with the observed data and another index based on the hypothetical situation, we are able to analyse the influence of education on poverty beyond its impact on income. Finally we present the conclusions.

2. Theoretical preliminaries

Education influences not only the ability of individuals to acquire higher wages and income, but also their behaviour and decisions, which will increase the probability of success in reaching different basic needs. Both effects imply that education allows individuals to avoid or to escape from poverty conditions.

Let us start with the pecuniary effect of education on poverty, i.e. the income return to education. In the human capital literature, whose pioneers are Schultz (1961) and Becker (1964), education is seen as an investment of present resources (time opportunity cost and direct costs) in order to obtain future returns. Schultz argued that knowledge and skill are a form of capital, which is a result of "deliberate investment". Education, training, and health investment increase opportunities and choices available to individuals, by affecting the ability to do productive work. Schultz attributes the difference in earnings between people to the differences in access to education and health.

As for Becker, he assumes that individuals choose education to maximise the present value of expected future incomes before retirement, net of the costs of education. The return of the n^{th} year of education can be seen as the difference between the wage obtained with n years of schooling and the wage obtained with $n-1$ years of schooling. Based on this assessment, several estimations of schooling returns for different countries have been carried out by analysing the variation of wages with an additional year of schooling.

Another fundamental contribution to the human capital theory is due to Mincer (1974). The well-known Mincer equation and some extensions of it are based on the belief that higher investments in education by individuals will yield higher wage levels.

This simple version of the wage equation was followed by a number of extensions, among others by Hungerford and Solon (1987), whose main contribution was to highlight the non-linearity of the relationship between years of schooling and income described in the Mincer equation. Indeed, there exist the so-called 'sheepskin effects', which reflect higher increments in wage in those years of schooling that represent the culmination of an educational level (i.e. secondary or higher).

In this paper we will follow the main insight of human capital theory: education is an investment decision of individuals, which will bring them future returns.³ Here, we will separately consider such returns as pecuniary and non-pecuniary. In a given year t , the income of a household will fundamentally depend on the educational investments that family members have done up to t . Clearly, other factors such as composition of the household and characteristics of the members are relevant as well.

³ It is not to deny that individuals might consume education for the utility it brings to them, given its intrinsic value.

This leads us to specify a relationship determining the pecuniary returns of education as follows:

$$\ln Y_h = f(E_h, X_h, Z_h) \quad h = 1, \dots, N \quad (1)$$

where Y_h is the income of household h , E_h is a vector of educational variables inside the household (e.g. Schooling years of the head of the household, highest level of education reached by any member of the household), X_h is a vector of other characteristics of the head of the household (e.g. sex and age), and Z_h represents characteristics of the household (e.g. number of children and region).

Let us now focus on the non-pecuniary effect of education on poverty, which extends far beyond its influence on income. Certain decisions and the behaviour of individuals might be changed favourably as education increases, allowing people to avoid or escape from poverty. Specifically, a higher capability to make more convenient - crucial - decisions increases the probability of success in reaching basic needs.

In the literature of the economics of education, there are important contributions on the non-market benefits of education, among others by Becker (1965), Michael (1972), and Grossman (2005). According to Becker, education positively influences the efficiency of non-market sector production processes – household production -. It also influences certain decisions of individuals such as growth in consumption (savings) during the life cycle, quantity and quality of children, addiction to drugs, etc.

Michael analyses the impact of schooling on the demand for commodities and market goods. More educated people become more efficient, so that they face lower marginal and average costs for each commodity. Finally, Grossman highlights the influence of education on the increase of production efficiency and allocative efficiency. To illustrate the first aspect, production efficiency, he uses the example of health, and concludes that “an increase in schooling is predicted to increase the quantity of health demanded but to lower the quantity of medical care demanded”. As for efficiency in allocation, his point is that more educated people are able to pick a better combination of inputs that gives them more quantity of output.

We will focus here on the non-market benefits of education that are related to poverty, specifically, those educational impacts on basic needs. Formally, we define the probability of an individual i to reach the basic need j (P_{ij}) as a function of a vector (E_i) of educational variables, income (Y_i),⁴ and a vector (X_i) of other characteristics of the individual.

$$P_{ij} = f_j(E_i, Y_i, X_i) \quad (2)$$

There are several reasons to support (2), i.e. to support the hypothesis that benefits of education are not limited to the greater possibilities for individuals to obtain higher incomes. Education enhances the ability to receive adequate nourishment: a well-

⁴ Any empirical application must, of course, take in account problems of endogeneity in equation (3).

educated person is more likely to select the right food needed to attain proper levels of nutrition, even with little money. Likewise, a person with higher education is better informed and therefore has the option to adopt good habits that allow him to have a healthier life. Knowledge of the human body, and its functioning, allows the person - if he wants - to take better care of it. (Kenkel (1991), (Strauss (1990))).

A similar correlation with education applies to the capability to avoid premature mortality. Moreover, education may help to reduce criminality, as many of its causes, i.e. poverty, unemployment, excess idle time, and so forth, are alleviated by education (Yamada et al (1991)).

In addition, the capability of family planning has an obvious link with education, as familiarity with the reproductive system and contraceptive methods may help people prevent unexpected pregnancy (Michael and Willis (1976)). There is an impact on the desired number of children as well, for at least two reasons: higher opportunity cost of having children (forgone income for raising children is higher for an educated person) and preference for postponing the age to start breeding (while educational investment is taking place).

We conclude from the previous analysis that proper evaluation of an educational policy must include both the pecuniary and non-pecuniary effects on poverty conditions.

Finally, it is useful to briefly refer to the multidimensional measurement of poverty, since one of the motivations of this paper is to point out how incomplete the analysis of poverty is when using a single dimension (i.e. income). Bourguignon and Chakravarty (1999) attempted to take account of the different dimensions of deprivation to define and measure poverty by specifying a poverty line for each dimension of deprivation. For them, a person is poor if he is below at least one of these poverty lines. Formally, they constructed the following measure, which we apply in section 5.

$$P_{\mathbf{a}, \mathbf{b}, b}^n(X, z) = \frac{1}{n} \sum_i \left[I(x_{i1} < z_1) \left(1 - \frac{x_{i1}}{z_1} \right)^{\mathbf{b}} + b^{\mathbf{b}/\mathbf{a}} I(x_{i2} < z_2) \left(1 - \frac{x_{i2}}{z_2} \right)^{\mathbf{b}} \right]^{\mathbf{a}/\mathbf{b}} \quad (3)$$

Where x_{i1} and x_{i2} correspond to attributes of individual i , z stands for the corresponding poverty threshold of each attribute $j=1$ and 2 . $\mathbf{b} = 1$, $\mathbf{a} = 1$, $b > 0$, and $I()$ is an indicator function that takes the value one if $x_{ij} < z_j$ or zero if $x_{ij} = z_j$.

Another of many important contributions on the topic was done by Tsui (1994, 2002)), who worked out the axiomatic basis of multidimensional poverty indices. The author generalized the Foster&Shorrocks class of subgroup consistent indices to the multidimensional framework. His proposed measure is a “numerical representation of shortfalls of basic needs from some pre-specified minimum levels”. For more about multidimensional poverty measure see Bourguignon and Chakravarty (2003), Atkinson and Bourguignon (1982), and Deutsch and Silber (1995), among others.

3. Pecuniary effects of education

In this and in the next sections, we will employ micro-data from a Colombian database called “Quality of Life Survey” to estimate equations (1) and (2). The sample design of the survey allows researchers to analyse the data at the national level and by regions, not by cities. The National Department of Statistics (DANE) carried out this survey in the years 1997 and 2003. The pooling cross section data contains information for 31.745 households. The survey inquires about housing conditions, access and quality of water, characteristics and composition of the household, health, characteristics of children less than 5 years old, education (to members 5 years old or more), employment, life conditions of the household, and household spending.

3.1. Methodology

The drawback of OLS for the estimation of equation (1) is the required assumption of exogeneity of the schooling variable, i.e. it is uncorrelated with the error term in the income function. There is a vast discussion in the literature about two problems with this exogeneity assumption: first, the error term in the income equation reflects a number of unobserved factors like ability. As a result, the error term will be correlated with the schooling variable (omitted variable problem). Second, according to the theory, an individual makes his schooling decisions taking into consideration the expected return. Hence, if the returns to education change, the educational investment decision will change too. Consequently, schooling and income are two simultaneously determined variables.

The problem of endogeneity should be solved to obtain consistent estimations. Using an adequate Instrumental variable for schooling is one of the appropriate techniques to deal with this problem. The idea is to identify exogenous influences on schooling decisions. Harmon and Walker (1995) exploit the exogenous changes in the distribution of education of individuals due to the increase of the minimum school-leaving age. Angrist and Krueger (1991) employ the season of birth of individuals to provide instruments for schooling. They consider the fact that those students born at the beginning of the year start education at an older age than students born at the end of the year. Therefore, the first group reach school-leaving age earlier and may drop out after completing less schooling than individuals from the second group. Another example is Card (1993), who employs data on proximity to schools considering that individuals living close to an educational institution are more likely to attend school than those living far away.

In line with Harmon and Walker (1991), we have explored exogenous variations on the schooling attendance of individuals in Colombia. The first instrument reflects the great educational expansion that Colombia experienced since the middle of the fifties. Due to the governmental purpose to universalize primary education, the years of schooling of that cohort of individuals and the next cohorts increase significantly compared to earlier cohorts (this will be equivalent to considering a change in

minimum school-leaving age to be equal to 12 years). The second instrument reflects the negative impact on schooling of young parenthood. As explained, we are using data corresponding to heads of households. Specifically, we create a dummy to identify individuals that have become head of households before reaching the age at which secondary school is normally culminated.

We could use the Two-Stage Least Square method to estimate equation (1), which actually corrects the endogeneity problem. However, the analysis of the problem we are focused on – the influence of education on poverty - offers more interesting insights if we can distinguish this influence for different quantiles of our response variable distribution (household income in this case). For such a purpose, a conventional Least Square regression is not helpful, since it only captures the relationship between covariates and the conditional mean of the dependent variable. In contrast, “Quantile Regression”, an alternative econometric method introduced by Koenker and Basset (1978), captures the relationship between the covariates and any conditional quantile of the response variable. In our case, for instance, the method allows us to concentrate attention on the lowest income groups.

The following paragraphs offer a brief formal explanation of the quantile regression method (Koenker (2005)). For a random variable Y with probability distribution function $F(y) = \text{Prob}(Y \leq y)$, the t_{th} quantile of Y is

$$F^{-1}(t) = Q(t) = \inf\{y : F(y) \geq t\}, \quad t \in (0,1).$$

Thus, the median of a distribution (0.5 quantile) corresponds to $Q(1/2)$.

Recall that, for a random sample of Y , the sample median minimizes the sum of absolute deviations or residuals:

$$\text{Median} = \min_{e \in R} \sum_{i=1}^n |y_i - e|$$

Similarly, the t_{th} sample quantile may be written as

$$\mathbf{e}(t) = \min_{e \in R} \sum_{i=1}^n \mathbf{r}_t(y_i - e)$$

where $\mathbf{r}_t(y_i - e) = (y_i - e)[t - I((y_i - e) < 0)]$. $I(\cdot)$ is an indicator function equal to 1 if $(y_i - e) < 0$, equal to 0 otherwise.

Now, the linear conditional quantile function $Q(t | X = x) = x' \mathbf{b}(t)$ can be estimated as the solution of the t_{th} regression quantile $\hat{\mathbf{b}}(t)$:

$$\hat{\mathbf{b}}(\mathbf{t}) = \min_{\mathbf{b} \in \mathbb{R}^p} \left[\sum_{i: y_i \geq \mathbf{x}_i' \mathbf{b}} \mathbf{t} |y_i - \mathbf{x}_i' \mathbf{b}| + \sum_{i: y_i < \mathbf{x}_i' \mathbf{b}} (1-\mathbf{t}) |y_i - \mathbf{x}_i' \mathbf{b}| \right] = \operatorname{argmin}_{\mathbf{b} \in \mathbb{R}^p} \sum_{i=1}^n \mathbf{r}_t(y_i - \mathbf{x}_i' \mathbf{b})$$

The traditional OLS method provides an estimate of $\hat{\mathbf{b}}(\mathbf{m})$, which expresses the relationship between X and the conditional mean of Y . In contrast, the use of Quantile estimations allows us to obtain $\hat{\mathbf{b}}(\mathbf{t})$ for any quantile $\mathbf{t} \in (0,1)$, this is, the relationship between X and any quantile of the distribution of Y .

As discussed previously, the problem of endogeneity of the education level variable should be solved for the estimation of equation (1). In the literature of quantile regression, a more recent contribution by Chernozhukov and Hansen deals with this issue (Ch&H (2001, 2004, 2005)). They worked out a model of quantile treatment effect - QTE - under endogeneity and obtain conditions for identification of the QTE without functional form assumptions. This technique is known as *Instrumental Variable Model of Treatment Effect*, which modifies the estimation procedure of the quantile regression by introducing instrumental variables that correct for the endogeneity problem and allow us to obtain consistent estimators.

3.2. Results of the Instrumental Variable Quantile Regression

Equation (1) is related to the traditional Mincer wage equation. However, the dependent variable is not the wage of an individual but the log of the total income of the household. For the purpose of our analysis, this choice is more appropriate, as we have information for all households in the sample. This would not be the case if we would work with wages, where we would have information only for the employed persons. Moreover, our aim is to analyse poverty conditions, which are not determined exclusively by labour income of individuals, but by any available income for the individual or household.

We use as explanatory variables the level of education of the head of the household, the gender and age of the head, the urban-rural location of the house and the number of children younger than 18 years. As described before, two instrumental variables are used. The first one reflects the increase in the minimum school leaving age due to expansionary educational policies in the mid-fifties. The second one captures the negative impact on schooling of young parenthood, which also affects the school leaving age. In the schooling equation, these variables are significant and have positive and negative signs respectively (See table A1).

By using the Two- stage Least Square method we find that an additional year of schooling of the head of the household increases total income of the household by around 14,1% (see table A1 for the complete results).⁵ However, the quantile

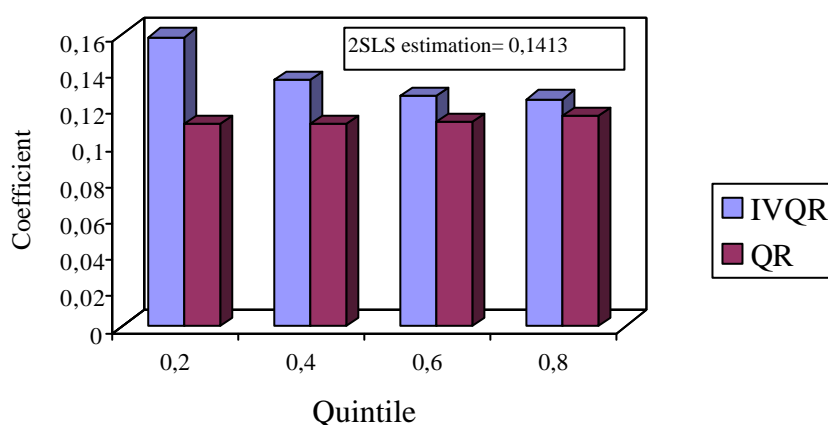
⁵ In the literature, there are several estimations of the monetary returns to education for different countries. However, they refer to the wage and not the household income as we do in this paper. For instance, Trostel et.al. (2002) estimated the returns to education for 28 countries, finding large cross-

regression technique suggests much more interesting results than this simple method based on the relationship between the covariates and the conditional mean of the response variable. Indeed, our estimates of the instrumental variable quantile regression confirm the suspected heterogeneity of the income effect of education across quantiles of the conditional household-income distribution.

Figure 2 shows the coefficient of schooling – returns to education – by quintiles (For the full estimation results see table A2). There are two interesting findings from the estimations. First, the differences in the coefficients for Quantile regression (QR) and Instrumental Variable quantile regression (IVQR) show that the endogeneity problem causes underestimation of the benefits of schooling in terms of income and that this underestimation is most pronounced for the lower quintiles. Second, the return of education is bigger for the lowest quintile and decreases as the quintile increases. This reveals that poorer people benefit more from the additional skills obtained through formal education. Chernozhukov and Hansen (2004) explain this by considering the quintile to which people belong as a proxy of their ‘unobserved’ ability: high ability individuals obtain higher earnings independently of their level of schooling, while low ability people profit more for each additional year of schooling. Apart from ability, there are other factors that increase with the quintile like social networks, more favourable family environment, among others, which help to explain in the same way the decreasing tendency of the IVQR schooling coefficients.

Ch&H suggest an additional and simple explanation: rational individuals invest in education until the point where the cost of schooling equals the returns. Recognizing that cost depends negatively on ability, we should expect that returns also decrease with ability.

Figure 2. Returns to education by quintiles of income



The estimations of the effects of the other variables in equation (1) are shown in table A2. The results can be interpreted as follows.

country heterogeneity of such returns: the lowest being 1.9% for Netherlands and the highest 19% for Philippines. Our results are comparable with those for USA, Ireland and Australia. In addition, Psacharopoulos and Patrinos (2004) presented estimations of private returns of investment in education for Latin America by educational levels: primary 26%, secondary 17% and higher 19%.

- For all quantiles, the coefficient of gender is negative. This means that households whose head is a woman are more likely to have less income. However, the coefficient slightly decreases for higher quantiles of distribution, which suggests that the disadvantage of female heads with respect to male heads belonging to the same income quantile is less severe when comparing households from the upper tail of income distribution.
- Households living in urban areas tend to have more income than in rural areas. Contrary to the case of gender, the coefficients reveal a higher disadvantage of rural households belonging to the upper tail of distribution. This result is consistent with the poverty measures for Colombia, according to which the inhabitants of rural areas are significantly poorer than those in urban areas: 68% (28%) of the rural population is poor (poverty-stricken), compared to 47% (14%) in urban areas.⁶
- The coefficient corresponding to the variable ‘number of children less than 18 years old’⁷ is positive and decreasing as the income quantile increases. One may expect that the coefficient has a negative sign instead, since children normally do not contribute to total income. This is the case when we re-do the regression using as response variable per capita income instead of total household income. We also observe in this second case that the coefficient becomes slightly more negative as the quantile increases.⁸

These results lead to at least a couple of questions.

First, why is the coefficient positive for all quantiles when the response variable is *log total income*? A tentative answer is that the more children there are, the higher is the need for disposable income. This might motivate parents to increase their labour supply.

Second, why does the coefficient decrease from 0.11 to 0.04 from the lowest to the upper tail? A possible answer is that children from the lower end of the distribution tend to enrol earlier into the labour market, contributing to the household income whereas children from the upper tail do not.⁹

4. Non-pecuniary effects of education

In this section we analyse the effects of education on two different non-income dimensions of poverty: health and housing conditions. In each case we control for income effects. The endogeneity problem that we had to deal with in the previous section is also present here. Again, we instrumented the endogenous variable years of schooling by using the two dummies reflecting changes in the school leaving age. In

⁶ National Department of Planning, 2004.

⁷ We chose 18 years as a threshold because it is at this age when individuals reach the ‘legal’ adult age in Colombia.

⁸ The results for percapita income are not reported in the appendix. They go from -0.2154 for the lowest tail to -0.2546 for the upper tail.

⁹ It is also interesting to note that the coefficient is slightly less negative for the lowest tail than for the upper tail when the response variable is log income per capita. The same explanation applies also in this case.

addition, we instrument the variable “income” by using the regional unemployment rate, as suggested by Ettner (1995). The unit of analysis is the head of the household.

4.1 Education and Health

In the light of the analysis derived from equation (2), we consider here three indicators of health: insurance affiliation, health prevention and health conditions of the heads of household. We start by examining the determinants of *affiliation to the health system* and specify an equation of the form:

$$HA_i = \mathbf{a} + \mathbf{b}S_i + \mathbf{j}X_i' + \ln Y_{ih} + \mathbf{n}_i \quad (4)$$

Where the response variable HA_i is a dummy equal to 1 if individual i belongs to the health insurance system, 0 otherwise. On the RHS we have S_i , years of schooling of individual i , gender and age of the individual (vector X), and $\ln Y_{ih}$, per capita income of household h , where i is the head of household h . Due to the endogeneity problem, the error term is equal to $\mathbf{n} = \mathbf{u} + \mathbf{e}$, i.e. the sum of an exogenous component and a component of unobserved factors related to schooling. Table A3 shows the results of the Probit model with instrumental variables.

All the covariates included in equation (4) are significant to explain the affiliation to the health insurance system. Additional years of schooling positively influence the probability of affiliation. Although the impact of income on this probability is also significant, we should not belittle the separate effect of education. The sources of this effect are, first, that more education enlarges the possibilities for an individual to get a formal job, which facilitates his affiliation to the health system. Second, education makes an individual aware of the importance of belonging to the health system in order to cope better with health risks.

We also observe that *i*) women are less likely to belong to the health system, *ii*) affiliation probability increases with the age of the individual, and *iii*) there is a marked disadvantage in affiliation of people living in rural areas.

Next we analyse the determinants of *health prevention*. The estimated equation is similar to (4), but we now define the dependent variable – health prevention –, as a dummy variable equal to 1 if individual i goes to the doctor for prevention at least once a year, and to 0 otherwise. On to the RHS we add a dummy variable to control for individuals who belong to the health system (equal to 1 if he belongs, to 0 otherwise). See Table A3 for the results.

As expected, education has a positive influence on the tendency of people to engage in health prevention. Knowledge of the functioning of the human body and of certain environmental risks makes people aware of the relevance of acquiring regular prevention habits. Thus, we can conclude that there is a separate and direct effect of education on health apart from the income effect. Put differently, although higher prevention is clearly related to higher income, there is a positive influence of education on prevention even among low-income groups.

The results of Table A3 also allow us to conclude that women are more cautious than men and that older people - either for obligation or responsibility - tend to develop higher prevention habits than young people (who face less risk of acquiring illnesses). Again, there is an advantage of urban heads of households with respect to rural heads in prevention habits.

Finally, we relate *health conditions* of individuals to their educational level. The equation to be estimated is similar to (4), but we now define our dependent variable - health conditions - as a dummy equal to 0 if the individual reports bad or average (not bad or good) health conditions and equal to 1 if the individual reports good or very good health conditions. Moreover, we include on the RHS a dummy variable indicating whether the individual lives in a polluted environment or not.

The results of the instrumental variables Probit model are shown in Table A3. We find that schooling has a significant effect on health conditions, and that this effect is separate from the significant income effect. In addition, we find that women are more likely to present health problems than men, inhabitants of urban areas present better health condition levels and, not surprisingly, health conditions worsen with age. The dummy variable indicating a polluted environment of the house is significant and has the expected sign.

We conclude from the three previous estimations that, even after controlling for income, the level of education plays an important role in modifying the behaviour and the decisions of people with respect to their health. As labour is the main asset of poor people, any factor that favourably affects the quality of such an asset (e.g. direct investment in health, indirect investment in health through educational investment), happens to be relevant in fighting poverty. Moreover, health is important not only for its instrumental value, but also for its intrinsic value: to be healthy is an end itself, not only a mean to reach other goals.

4.2 Education and Housing

We now regress an index of housing conditions on schooling and income. This index is based on information about access and quality of utilities, material of walls and material of the floor.

We find that differences in housing conditions are not only explained by differences in income between households, but also by the schooling level of the head of the household (see the results on table A3). This separate effect of schooling can be explained by the fact that better-educated people have more appropriate spending priorities than less -educated people: comparing households with the same income, housing conditions are better the higher is the educational level of the head of the household. In addition, more educated people have a better access to the credit market, which creates the possibility to improve the conditions of the house. If we had information about permanent income, it is likely that this relationship between housing conditions and income would be more strongly perceived.

5. Simulation

In this section we will simulate a situation in which every head of household manages to reach 11 years of education as a minimum (complete secondary school). We assume that individuals with at least complete secondary school are more likely to overcome poverty conditions. The first step for the simulation is to calculate an index of Poverty for the head of households by using the observed information. For this purpose we have chosen one of the several multidimensional poverty indices suggested in the literature (see equation 5). Because of simplicity and data restrictions, the index of poverty considers three dimensions: health, housing and income. Obviously, education is another dimension of poverty, but it is not included because the purpose of the simulation is to check the impact of an improvement in education on the other dimensions of poverty.

The health dimension includes affiliation to the insurance system, prevention habits and health conditions as in section 4.1. The housing dimension combines access to utilities and physical conditions of the house. Finally, the income dimension is the proportion between observed income of an individual and the income poverty threshold (2 dollars of income).¹⁰

Equation (5) represents the aggregate poverty index that we use for the simulations. This index was proposed by Bourguignon and Chakravarty (B&CH) (1999) (See equation (3)).¹¹

$$P(X, z) = \frac{1}{n} \sum_i \sum_j I(x_{ij} < z_j) \left(1 - \frac{x_{ij}}{z_j} \right)^b \quad (5)$$

where $P \in [0,1]$; j denotes a given poverty dimension; i represents individuals from 1 to n ; x_{ij} is the observed level of dimension j of individual i ; z_j is the poverty threshold of dimension j ; I is an indicator function equal to 0 if $x_{ij} \geq z_j$ and equal to 1 if $x_{ij} < z_j$. Finally, $b > 1$.

After calculating the poverty index using the observed information, the second step consists of calculating a hypothetical P based on the results of the preceding section. Given the actual situation, we apply the coefficients obtained from the models in section 3, simulating that those heads of households with less than 11 years of schooling manage to reach at least this level of education.

¹⁰ The criteria of 2 dollars a day is highly criticized due to, among other drawbacks, its lack of clear connection to the real acquisitive power of the people. However, our main purpose is not to provide an accurate measure of poverty, but to observe the changes that an improvement in education has on each poverty dimension and on the aggregate.

¹¹ In our case, $b=1$ and $\alpha=\beta$.

In order to obtain the hypothetical P , we should consider the direct and indirect effects of additional years of education on the poverty dimensions. Thus, we consider both arrows (*) and (**) of figure 1 in the introduction of the paper. Indeed, additional years of schooling increase income, and this has a positive impact on the possibility of an individual for satisfying the different basic needs - multiplicative effect of education captured by combining the coefficient of S in the income equation and coefficients of hY in the estimations of section 4 -. Furthermore, additional years of schooling have a direct impact on the enjoyment level of basic needs – reflected in the coefficient of S in each estimated equation of section 4 -. These two channels of impact contribute to pull down the aggregated P .

Table 1 contains the results of this simulation. The first column presents the observed aggregate poverty index (P) and the observed poverty index for each dimension j . The second column shows the indices re-estimated under the hypothetical situation previously mentioned. Finally, the third column shows the value of the hypothetical indices when we exclude the direct impact of education on each of the basic functionings.

Table 1. Poverty Indices (Simulation)

	Observed Poverty index	Hypothetical Poverty index	Excluding direct effect	Decrease
P	0,40	0,23	0,33	0,17 (0,07)
P_house	0,11	0,08	0,10	0,03 (0,02)
P_health	0,21	0,13	0,20	0,08(0,07)
P_income	0,10	0,03		

The results show that the hypothetical educational improvement leads to a decrease of the index of poverty by 17 percentage points (the difference is statistically significant). If we were to consider only the pecuniary impact, we would be ignoring a relevant non-pecuniary impact on poverty conditions of individuals – the decrease in poverty would be underestimated by about 10 percentage points. Such an underestimation would be higher if we were able to consider other basic functionings in the poverty index.

This simulation clearly excludes several important channels of impact of education, which are expected to have an influence on poverty conditions as well, e.g. family health, attainment of desired family size, preference for postponing breeding, crime reduction, among others. Furthermore, a dynamic analysis (information of cohorts for several periods) might offer more accurate quantitative results of the impact of education on poverty.

However, the static analysis of this paper is useful to examine the scope of an educational policy, whose influence on poverty has a double nature: indirect - the increment on income and wages -, and direct – the increase in the level of enjoyment of the different basic needs -.

6. Conclusions

This paper makes two main contributions. First, we use the recently developed technique of instrumental variables quantile regression (IVQR) to analyze the pecuniary effects of education. Second our analysis highlights the non-pecuniary returns to education: the resources invested in education bring future returns to individuals, not only reflected in monetary earnings, but also in higher levels of satisfied basic needs.

The IVQR is a very helpful method especially when one is interested in the lowest or highest tails in the distribution function of the dependent variable. In fact, there is no reason to believe that the estimates of the effects of education on the income of households or individuals do not vary between the lowest and the upper tail of the income distribution. Indeed, our estimates confirm the suspected heterogeneity of the income effect of education across quantiles of the conditional household-income distribution.

There are two interesting findings from the estimations of the income equation. First, the differences in the coefficients for quantile regression (QR) and instrumental variable quantile regression (IVQR) reveal that the endogeneity problem causes underestimation of the benefits of schooling in terms of income. Second, the return of education is bigger for the lowest quintile and decreases as the quintile increases. This reflects the fact that people from the lower quintiles benefit more from the additional skills obtained through formal education. Following Chernozhukov and Hansen (2004), we may consider the quintile to which people belong as a proxy of their 'unobserved' ability: high ability individuals obtain higher earnings independently of their level of schooling, while low ability people profit more for each additional year of schooling. Apart from ability, there are other factors that increase with the quintile like social networks, more favourable family environment, communication skills, early intellectual stimulation, among others, which help to explain in the same way the decreasing tendency of the IVQR schooling coefficients.

With respect to the second contribution, this paper was meant to highlight the relevance of several channels of impact of education on poverty. More specifically, it aimed to draw attention to the non-pecuniary returns of education, whose consideration allows us to be more accurate in analysing the benefits of educational policies on poverty.

Returns to education are not limited to the pecuniary impact on wages and income. There are relevant non-pecuniary returns, as a result of the influence of education on the behaviour and abilities of individuals. Indeed, certain crucial decisions related to poverty conditions are positively influenced by education. Specifically, education affects health, mortality, fertility, housing conditions, and recreation, among others. Some of those channels of impact were analysed in this paper.

As far as health is concerned, we found that health affiliation, health prevention and health conditions are positively related to education, after correcting for income levels. Individuals with more years of schooling tend to acquire better health habits,

given their level of income. This direct effect might be due to the fact that education makes them aware of the importance of health.

We also included in the analysis the relationship between housing conditions and education of the head of the household. We found that, after controlling for income, the higher the education levels of the head, the better the housing conditions. This may be due to better criteria for establishing spending priorities of well-educated people.

Finally, results of the simulation show that an educational improvement consisting of all individuals managing to reach at least 11 years of education, would reduce the poverty index by around 17 percentage points. If we were to consider only the pecuniary impact of the hypothetical educational improvement, we would be ignoring a relevant non-pecuniary impact on poverty conditions of individuals – the decrease on poverty would be underestimated by about 10 percentage points (table 1).

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Table A1

	Reduced equation	2SLS
	Dep var= Schooling	Dep var=Log total income
Schooling		.1413218 (.0122025)
Dummy 50	1.189957 (.0953474)	
DummyYP	-1.171548 (.112476)	
Age	-.0744852 (.0031954)	.0196414 (.0012217)
Sex	-.4461729 (.0541585)	-.2181571 (.0140274)
Urban-rural	4.372026 (.0587737)	.4681196 (.0559549)
Children <18	-.676878 (.017929)	.0756694 (.0086042)
Dummy2003	1.15873 (.0583689)	-.1274449 (.0199918)
Constant	7.551146 (.2169359)	11.498 (.1141266)
R-squared	0.2939	0.3188
Number of obs	31745	31745

Table A2

Dependent variable: Log of household income

Instrumental Variable Quantile regression

	0,2		0,4		0,6		0,8	
	Coefficient	Std error	Coefficient	Std error	Coefficient	Std error	Coefficient	Std error
Schooling years	0.1584	0.0127	0.1349	0.0112	0.1261	0.0139	0.1248	0.0144
Age	0.0191	0.0012	0.0192	0.0011	0.0204	0.0014	0.0221	0.0014
Sex	-0.2157	0.0183	-0.2291	0.0138	-0.2060	0.0152	-0.1898	0.0171
Urban-Rural	0.3504	0.0633	0.4202	0.0511	0.4019	0.0612	0.4084	0.0687
children<18	0.1108	0.0090	0.0767	0.0086	0.0565	0.0127	0.0407	0.0116
Dummy2003	0.1805	0.0366	-0.0330	0.0243	-0.2200	0.0221	-0.4896	0.0213
Constant	104.236	0.1187	113.744	0.1026	119.579	0.1334	125.834	0.1345

Quantile regression

	0,2		0,4		0,6		0,8	
	Coefficient	Std error	Coefficient	Std error	Coefficient	Std error	Coefficient	Std error
Schooling years	0.1108	0.0018	0.1107	0.0014	0.1119	0.0013	0.1152	0.0014
Age	0.0143	0.0005	0.0170	0.0004	0.0191	0.0004	0.0212	0.0005
Sex	-0.2292	0.0160	-0.2283	0.0132	-0.2104	0.0131	-0.1945	0.0151
Urban-Rural	0.5915	0.0225	0.5246	0.0165	0.4655	0.0158	0.4571	0.0177
children<18	0.0815	0.0052	0.0608	0.0045	0.0477	0.0044	0.0334	0.0048
dummy2003	0.2813	0.0244	0.0058	0.0180	-0.2030	0.0167	-0.4814	0.0193
Constant	108.826	0.0446	115.682	0.0345	120.732	0.0333	126.683	0.0373

Table A3

EDUCATION AND NON- INCOME POVERTY DIMENSIONS			
Dependent variable: Health conditions		Dependent variable: Health prevention	
Instrumental Variables Probit model		Instrumental Variables Probit model	
S	.1236153 (.0161669)	S	.0737074 (.0094003)
Mg eff	.0431564	Mg eff	.031564
LnY	.2745277 (.0692084)	LnY	.0441824 (.0213231)
Age	-.0186752 (.0020069)	Age	.0084037 (.0014234)
Sex	-.2466817 (.0215296)	Sex	.3061479 (.0320945)
No pollution	.0165825 (.0223094)	Dummyaffiliation	.5898898 (.0356782)
Urban- Rural	-.319354 (.062064)	Urban- Rural	.0813698 (.0461234)
_cons	-2.531904 (.6831546)	_cons*	-2.227626 (.2059349)
Log pseudo-likelihood =-111655.7 Wald chi2(6)= 5649.65		Log pseudo-likelihood =-32730050 Wald chi2(6)= 1139.58	
Dependent variable: Affiliation to Health system		Dependent variable: Housing conditions	
Instrumental Variables Probit model		Instrumental Variables (2SLS) regression	
S	.051632 (.0201341)	S	.0901228 (.0140219)
Mg eff	.0199982		
LnY	.401271 (.0813611)	LnY	1.064.307 (.1030321)
Age	.0113901 (.0026972)		
Sex	-.0124728 (.0205703)		
Urban- Rural	-.0587601 (.070713)	Urban- Rural	-.2266381 (.1241517)
_cons	-5.22538 (.7708423)	_cons	-12.15188 (1.227068)
Log pseudo-likelihood =-111618.58 Wald chi2(5)= 1965.21		R-sq = 0.4905 F (3, 20746)=3173.39	
General notes:			
Endogenous variables: S (years of schooling) and LnY (log of percapita income).			
Instruments: Dummy50 (reflecting educational expansion in Colombia), Dummy81 (reflecting young parenthood), Unemployment rate of the region.			
Standard errors in parenthesis			
* Non-significant			