The Effect of Labor market Conditions and Family Background on Educational Attainment of Spanish Youngsters[1].

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Abstract

In this paper we analyze the effects of family backgrounds, labor market conditions and household structure in educational attainment and enrollment in post-compulsory education of Spanish youngsters during the nineties. For these purposes, we use a sample of data drawn for the first four waves of the European Panel Household Survey (ECPH), coupled with labor market data.

1 INTRODUCTION

In the last two decades, the level of educational attainment in Spain has experimented a high increase. This educational expansion has some special characteristics compared to other European countries: college attendance have risen from 18 per cent of the population between 18 and 24 years old to 41 per cent in 1999[1]. However, the percentage of the population that has attained at least upper secondary education is lower that the media of OCDE (only 60 per cent of 25 to 34-year-old compared to 74 per cent of OCDE media in 2001, see OCDE (2002)). Moreover, participation in post-compulsory school, although it has also improved, it is far away from OCDE recommendations (see Petrolongo and San Segundo (2001)). This spectacular and also unbalanced increasing has produced an over-education phenomenon in the sense that workers' educational attainments are higher than the skill requirements of jobs, see Dolado et al (2000).

In searching for explanations, we start with human capital models (Becker (1964)), in which individuals decide the optimal amount of education by weigthing up the costs and the benefits of an additional unit of schooling. Both costs and benefits are influenced by individuals characteristics, but also by variables that vary at the aggregate level (labor market conditions, public performance). On the one hand, family backgrounds are strong predictors of final educational outcomes of young adults (see Haveman and Wolfe (1995) for a complete review of American Studies), affecting strongly the cost of education, see Card (2001). On the other hand, it can be observed that public authorities have largely encouraged educational expansion supporting tuition cost and also promoting the creation of new universities (mostly public). With respect to economics incentives, returns to education are lower than in other European countries (see Dolado et al (2000)). Finally, unemployment rate also plays an important role affecting both costs and returns [see Kodde (1998) and Fernandez and Shioji (2001)]. Firstly, the higher rates of young unemployment (until 40 per cent in some areas) reduce substantially the opportunity costs. Moreover, the fact that unemployment rates of high-educated people are lower than those of non-educated people encourages to invest in education. Finally, higher unemployment can also reduce the benefits of education and, therefore, it discourages demand for education.

For the US and UK, many empirical works have analyzed the relationship between educational outcomes of the children and family background using a wide variety of controls (see for example Altonji and Dunn (1996) for the US and Ermish and Francesconi (2001) for UK). By contrast, in Spain this relationship remains unexplored. It has only been documented using cross-sectional data (Labour Force Survey (EPA), Budget Household Survey (EPF)), yielding some measurement errors in family background variables (Cameron and Heckman (1998b)). Among these studies we find Gonzalez and Davila (1998) and Beneito et al (2001) based on the EPF and Albert (1998) based on the EPA.

[1] See Human Capital Database from the Valencian Institute of Economic Research (IVIE).

Few attention has been devoted to the role of labour market conditions in educational decisions. However, these studies generally tend to confirm that investment education decisions respond to economics incentives (see Freeman (1986)). By contrast, there are contradictory evidence on the effects of unemployment. Beths-McFarland (1995) use panel data analysis to investigate the role of unemployment in explaining community enrolment and they find positive evidence. Card and Lemieux (1997) find that the unemployment population ratio reduces the proportion of youth attending school, but when they try to explain changes over time, labour market measures loose their explanatory power. For the Spanish economy, Martinez and Ruiz Castillo (1998) obtain negative effects.

In this paper we analyze the determinants of educational attainment and enrolment in post-compulsory education in Spain during the nineties using a new sample of data drawn for the first four waves of the European Panel Household Survey (ECPH). This dataset allow us both better family controls and measurement of educational attainment than previous studies. Moreover, we analyze the role played by labor market conditions, with special attention to unemployment prospects. More specifically, we try to disentangle the mechanism through unemployment affects educational decisions. For this purpose, following Petrolongo and San Segundo (2001) and Fernandez and Shioji (2000), we use a wide variety of unemployment rates obtained from the INE and a new dataset, the Human Capital Database from IVIE.

Our results show that children education achievement is strongly related to parents education, although the presence of marital sorting by schooling (specially in the mothers) does not allow us to distinguish whether father's or mother's education play more important role. Youngsters from poor families find also difficulties in accessing higher levels of education. Moreover, family structure measures are relevant. Our results suggest that single mother's children have less probability to obtain higher education levels. With respect to the decision of continuing studying, the most relevant determinants are the region and the parental education. Unemployment prospects have also effects in children's educational outcomes, specifically in the decision of continuing in school. Moreover, our results suggest that unemployment prospects affect the demand for education through dimishing the cost more than increasing the returns to education.

In the next section, we develop a very simple model in order to illustrate the theoretical framework. The specification of the empirical model are discussed in section 3. In section 4 we describe the data and the variables used in the analysis. In section 5 we present the results.

2 THE THEORETICAL FRAMEWORK.

We consider a human capital model [Becker (1964), Card (2001)], in which individuals reach an optimal schooling decision by balancing the benefits of higher education against the cost. We incorporate to this framework the possibility of

experiencing unemployment. In this sense, as it was shown by Kodde (1986), Nickell (1979) and more recently by Rice (1999), and Fernandez and Shioji (2000), unemployment prospects play and important role in this decision.

Consider a two-period model, where $i = \{1, 2\}$, and 1 stands for the first period and 2 for the second one. In the first period, individuals make their educational choice. More specifically, if we denote by T the available time in the first period, they divide it by choosing a $s \in [0, T)$, where s is the time devoted to education and $T - s$ the time devoted to labor supply. The individual faces a direct cost of education denoted by $p_s(\mathbf{X})$, where X is a vector which individuals characteristics and family background. In the sake of simplicity, we denote it by p_s. We assume that individuals can experience unemployment in the first period when they are young, although it does not depend on the educational choice, that is, individuals find a job with probability π_1 or become unemployed with probability $(1 - \pi_1)$. In this sense, the latter probability can be considered as a proxy of "young unemployment" rate. We assume that there are not unemployment benefits. Finally, when individuals work they earn a fixed wage w_1.

In the second period, individuals' level of education is determined by the previous period choice. We also assume that there exists unemployment in the second period, which in contrast with the first period depends on the level of education (Kodde, 1986). More specifically, individuals find a job with probability $j(s)$, where $\frac{\partial j(s)}{\partial s} > 0$ and $\frac{\partial^2 j(s)}{\partial s^2} < 0$. Therefore, $(1 - j(s))$ can be considered as a proxy of the "adult unemployment" rate for different levels of education. On the other hand, we denote by $f(s)$ the individuals' earnings, where $\frac{\partial f(s)}{\partial s} > 0$ and $\frac{\partial^2 f(s)}{\partial s^2} < 0$, that is, they increase with the level of education[2]. We suppose that individuals receive a constant amount of social benefits, c, when unemployed. Finally, we assume perfect capital markets with interest rate, R.We suppose that an individual receives exogenous transfers from parents in each period, A_i, $i = \{1, 2\}$.

We now move to specify the budget equation for each period. In both periods, the budget equation depends on unemployment status. Hence, individual's consumption in period $i = \{1, 2\}$ is denoted by c_{ie} and c_{iu} when employed and unemployed, respectively. In the first period, the budget equation is stated as follows:

$$c_{1e} = -p_s s + w_1(T - s) + A_1 \quad (1)$$

$$c_{1u} = -p_s s + A_1 \quad (2)$$

In the second period, the budget equation is:

$$c_{2e} = f(s) + A_2 \quad (3)$$

$$c_{2u} = c + A_2 \quad (4)$$

[2] For simplicity, individuals' earnings are independent of their previous experience.

In this problem the decision reduces to choosing the level of education in the first period to maximize lifetime expected utility. We assume that the individuals have a separable utility function over the two periods:

$$\begin{aligned} U(c_1, c_2) &= EU(c_1) + \beta EU(c_2) = \pi_1 U(c_{1e}) + (1-\pi_1)U(c_{1u}) + \\ &\quad \beta[j(s)U(c_{2e}) + (1-j(s))U(c_{2u})] \end{aligned} \tag{5}$$

where $EU(\cdot)$ is individuals' expected utility and β is a positive constant discount rate.

For the sake of simplicity, we also assume that $U(c_i) = c_i,\ \{i = 1, 2\}$, that is, individuals are risk neutral. Substituting (1)-(4) in (5), the solution to this problem is given by the following first order condition (FOC) in which

$$j'(s^*)\left[f(s^*) - c\right] + f'(s^*)\, j(s^*) = \frac{1}{\beta}\left(\pi_1 w_1 + p_s\right) \tag{6}$$

The left hand side of (6) reflects the marginal benefits of investing in an additional unit of education. An additional unit of education increases the earnings and, secondly, it diminishes the probability of becoming unemployed in the second period. On the other hand, the right hand side of (6) gives the marginal cost. It is composed of tuition cost and foregone earnings, which are affected by the possibility of experiencing unemployment in the first period.

Let us see how our model can help to analyze the different effects of unemployment on educational attainment. We first consider the simple case in which the probability of finding a job in second period is equal to 1, i.e. $j(s) = j = 1$. In this case, the FOC (6) reduces to:

$$\pi_1 w_1 + p_s = \beta f'(s) \tag{7}$$

We also assume perfect capital markets, which implies that the discount rate is equal to the inverse of the interest rate. Notice that in this case, the marginal cost of schooling are given by foregone earnings and tuition cost, but, in contrast with traditional human capital theory, are offset by the probability of becoming unemployed when individuals are young. It is important to note that the foregone earnings depends on the probability of becoming unemployed when the individual is young[3]. More precisely, let $f(s) = s^\gamma$, with $0 < \gamma < 1$. Then:

$$s^* = \left[\frac{R(\pi_1 w_1 + p_s)}{\gamma}\right]^{\frac{1}{\gamma - 1}} \tag{8}$$

Therefore, the impact of young unemployment and tuition cost on the optimal level of education, respectively, are given by:

[3] Notice that this result differs from human traditional theory (Willis (1986), Card (2000)).

$$\frac{ds^*}{d\pi_1} = -\frac{1}{1-\gamma}[\frac{R(\pi_1 w_1 + p_s)}{\gamma}]^{\frac{\gamma}{\gamma-1}} w_1 < 0 \quad (9)$$

$$\frac{ds^*}{dp_s} = -\frac{1}{1-\gamma}[\frac{R(\pi_1 w_1 + p_s)}{\gamma}]^{\frac{\gamma}{\gamma-1}} < 0 \quad (10)$$

In the other hand, "young unemployment" encourages additional education through lowering the opportunity cost of education. On the other hand, higher tuition costs desmotivate individuals enrolment.

We move now to another extreme position in which the probability of finding a job in the second period does not depend on the level of education, that is, $j(s) = j$, and therefore $j^{'}(s) = 0$. Furthermore, we rule out young unemployment, i.e., $\pi_1 = 1$. Then, FOC (6) transforms into:

$$p_s + w_1 = \frac{1}{R} j f^{'}(s) \quad (11)$$

Using the former earning function:

$$s^* = [\frac{R(w_1 + p_s)}{j\gamma}]^{\frac{1}{\gamma-1}} \quad (12)$$

In this case, we can evaluate the impact of "adult unemployment" and tuition cost, respectively:

$$\frac{ds^*}{dj} = \frac{1}{\gamma-1} j^{-2} [\frac{R(w_1 + p_s)}{j\gamma}]^{\frac{\gamma}{\gamma-1}} \frac{R(w_1 + p_s)}{\gamma} > 0 \quad (13)$$

$$\frac{ds^*}{dp_s} = -\frac{1}{1-\gamma}[\frac{R(w_1 + p_s)}{j\gamma}]^{\frac{\gamma}{\gamma-1}} < 0 \quad (14)$$

The effect of "adult unemployment on the optimal level of education is the opposite to "young unemployment". This is so, because higher adult unemployment diminishes returns to education and hence, reduces optimal investment in education. The effect of tuition cost are the same as before.

Finally, we assume that the labor market outcomes of investing on education depends on the probability of becoming employed[4]., $j(s)$ More precisely, consider the following function, $j(s) = [1 - e^{-\phi s}]$, with $0 < \phi < 1$. Furthermore, we also assume earnings are independent of s, i.e., $f(s) = B$ and "young unemployment" is ruled out. Therefore, the FOC is given by:

$$p_s + w_1 = \frac{1}{R}[\ln e^{-\phi s}(B + A_2 - c)] \quad (15)$$

[4]See Kodde (1986) and, more recently, Card (1995).

The effects of unemployment-education elasticity, ϕ, and the tuition costs respectively are evaluated by the following expressions[5]:

$$\begin{aligned}\frac{ds}{d\phi} &= \frac{1}{\phi^2}[1+\ln[\frac{R(p_s+w_{1)}}{\phi(B-C)}]>0\\ \frac{ds}{d\phi} &= -\frac{1}{\phi}[\frac{\phi(B-C)}{R(p_s+w_{1)}}]<0\end{aligned}$$

Higher probability of finding a job stimulates college-going behavior. By contrast, as before, higher tuition costs desencourage demand for education.

3 THE ECONOMETRIC MODEL.

In this section, we firstly summarize the most important empirical strategies that have been followed in the literature. Finally,we describe how will estimate the theoretical model presented in section 2.

3.1 Empirical models.

Modelling educational choices is subject to some methodological difficulties, which explains that different approaches have been adopted by the literature. Firstly, the final level of education can be defined as a sequential process during which certain number of decisions are made at different points of time. Moreover, it is necessary an econometric specification to interpret the estimators in a human capital framework. In addition , it is also necessary to make some assumptions either on when the decisions are taken and also the relevant factors. Let us summarize the most relevant approaches

One approach widely adopted is to divide the educational career into a finite number of transitions and analyze the probability of final educational attainment as the product of transition probabilities [Mare (1980)]. The advantage of this approach is that it allows to relate current school choices with contemporaneous aspects, such as labour markets conditions or income, but panel data are required in order to obtain variables in each stage (or at least, retrospective reports of childhood events). On the other hand, a disadvantage of this approach is that ignores the cumulative nature of schooling decisions because it is assumed that each transition is independent of the choice made in previous years. As a results, it is difficult to interpret this transition in the context of human capital model. Moreover, this approach focus on a non random sample of individuals [6], that produces problems of selectivity bias[7].

[5] For this function, $\frac{ds}{d\phi}$ is positive as long as the returns to education are $\in [\phi(B-C), \phi(B-C)e)$. See Kodde (1986) for a more general function.

[6] See Cameron and Heckman (1998) for a thoroughly analysis of this question.

[7] Other studies, based on Mare (1980), focus on one particular transition in isolation from

Another approach analyses the probability that the individuals successfully completed all previous transitions up to the last one observed. The ordered probit is frequently used to estimate the final grade attainment [see Lauer (2001)) and Chevalier and Lannot (2001)]. Cameron and Heckman (1998a) shows that an ordered probit can be used to estimate a human capital model under some assumptions. Firstly, there does not exist grade specific-shocks under transitions and the education choices are governed by just only one unobservable. Depending on data constrains, the research has measured alternatively the determinants at nearly sixteen and the outcome several years later, or measure determinants at different childhood stage (see Haveman and Wolfe (1995)). The problem of this approach is that it does not allow to disentangle really between the impact of explanatory variables at each stage of educational process.

Another problem arises due to some unobservable processes are jointly affecting both family backgrounds and children's attainments and, as a result they produce some biases in the estimators [Ermish and Francesconi (2001)]. To overcome this problem, different approaches have been followed. Firstly, some studies estimate the impact of some specific variables on the level of school attainment, controlling for a variety of other variables, in order to establish causal relationship. In this sense [see for example Cameron and Heckman (1998a) and Shea (2000)], focus on estimating the true causal family income effects on educational attainment. On the other hand, some studies use a wide variety of parental and regional variables available in a particular data set and attempt to identify which among them appear to be significantly related. Although these estimators are interesting, they must be interpreted with caution.

3.2 Empirical strategy.

The approach adopted in this paper is the following:

(i) We model educational choice using a discrete ordered probit model[8]. The ordered probit model, [as was shown by Cameron and Heckman (1998a)] can be interpreted in a optimizing agents framework, as we propose in the theoretical model.

(ii) We focus on four groups of variables: individuals controls, family background, household composition and labour market conditions in order to determine which of them appear to be significant. We make this decision for several reasons. Firstly, there do not exist too many Spanish researches that analyze in a complete manner determinants of school attainment of the children [exception of Albert (1998), Beneito et al (2001)], mainly family structure. Moreover, data constraints make difficult to establish a causal effect relationship. The ECPH (see next section for a detailed explanation on this dataset) have a lot of advantages, but have also some shortcomings. It is a relatively "young panel", only has four waves and it does not contain retrospective information on individuals.

other transitions (for example, Willis and Rosen (1979) and Manski and Wise (1983) examine the transition from high school to college attendance). They have the same problems.

[8] Although in our theoretical model s is defined as continuos, in our empirical model we define it as discrete because in the EHPS is offered in this way.

This fact difficulties to obtain instruments that allow us to control the effect of unobserved factors.

(iii) the former restrictions provoke that we must measure the determinants when individuals are nearly sixteen (see next section).

Let us now relate the theoretical model with the empirical one (see section 2).

The empirical counterpart of $p_s(X)$ are three groups of variables: individuals controls, family backgrounds and also household composition. For labour market conditions, measured as $f(s)$ and $j(s)$, π_1 and j, we use local labour market conditions at the moment the individual take the decision. More specifically, $f(s)$ includes wages to different levels of s, π_1 is approximated by unemployment rate for young people, but also by unemployment rate for adult people with primary school, j is approximated by unemployment rate for adult people and unemployment rates for different levels of education of are used as proxy $j(s)$ (see next section for a complete analysis of these variables).

The econometric model can be expressed as:

$$S_{ir}^{*} = \boldsymbol{\beta}_x \mathbf{X}_{ir}^{'} + \boldsymbol{\beta}_z \mathbf{Z}_{r}^{'} + U_{ir}, \tag{16}$$

where S_{ir}^{*} is a latent variable that represents the optimal level of schooling of the *ith* individual in local market r, $\mathbf{X}_{ir}^{'}$is a vector of individuals controls, family background and household composition, $\mathbf{Z}_{r}^{'}$ is a vector of labour market conditions in local market r, and $\boldsymbol{\beta}_x$ and $\boldsymbol{\beta}_z$ reflect the effects of family background and labour market conditions on educational attainment, respectively. Finally, U_{ir} is the error term normally distributed with mean zero and variance 1. We do not observe the latent variable, but the observed optimal educational choice can be modelled in the following way:

$$S_{ir} = l \text{ if } \mu_{l-1} < S_{ir}^{*} < \mu_l, \tag{17}$$

where l=1,2,....,L are educational levels and μ_l are the cut-off levels in the ordered probit model, with $\mu_0 = -\infty$ and $\mu_l = +\infty$ and $\mu_1 < \mu_2 < .....< \mu_L$ [see Maddala (1983)]. For more details about the educational attainment, see section 3. From the ordered probit model we can predict the probability of a person to be in every qualification level.

$$\Pr(S_{ir} = l \mid \mathbf{X}_{ir}, \mathbf{Z}_r) = \Phi[(\mu_l - [\boldsymbol{\beta}_x \mathbf{X}_{ir}^{'} + \boldsymbol{\beta}_z \mathbf{Z}_{r}^{'}]] - \Phi[(\mu_{l-1} - [\boldsymbol{\beta}_x \mathbf{X}_{ir}^{'} + \boldsymbol{\beta}_z \mathbf{Z}_{r}^{'}]] \tag{18}$$

where Φ is the cumulative distribution of the normal distribution.

4 DATA AND VARIABLES.

The estimation of the former model requires data on individual's characteristics, family background and labor market variables. For the first two types of

variables, data is taken from the four waves of ECHP. Since 1994, the ECHP has been designed to compare different aspects of European countries and annually interviews a representative sample of 80.000 households, of which 8.000 are Spanish. The same individuals are reinterviewed each successive year, and if they leave their original households to form a new one, all adults members of these new households are also interviewed. Similarly, children in original households are interviewed when they are sixteen.

The ECHP is the unique longitudinal dataset available for Spanish economy, which clearly provides a better measurement of family background than the Spanish Labor force Survey (EPA), the other dataset available for this period. Nevertheless, the EPA has a longer sample and it is available for the period 1987 onwards.

In order to capture the different effects associated with unemployment prospects, individual records files are matched with several unemployment rates. We use the unemployment rates for those aged "16-24" (by area[9] and sex) and "older than 25"[10] (by zone and sex), which are collected from the statistics published by the National Institute of Statistics (INE). We also use the unemployment rates for different educational degrees, that were obtained from the Human Capital Database from the Valencian Institute of Economics Research (IVIE) (also disaggregated by sex and zone)[11]. See the next subsection for a detailed description of these variables.

We restrict our analysis to individuals (i) aged 15-18 in December of 1994, (ii) who live with at least one biological, adoptive or step-parent and (iii) we can observe their educational attainment in 1996-1997. The condition (ii) is imposed in order to match data on family background from the parents records to their children. This fact also allows us to obtain measurement of other family backgrounds characteristics unavailable otherwise (such as the number of siblings, parental education)[12]. Since 98 per cent of the ample individuals live with their parents when aged 15-18 (see Table A1 and A2 in the Appendix), this condition should not affect the randomness of the sample (Cameron and Heckman (1998a)). Conditions (i) and (iii) are imposed in order to match data on family background at the age they are more relevant, nearly sixteen[13]. In this sense, Chevalier and Lanot (2001) argue that the most relevant variables when they make their educational choice are nearly sixteen. Moreover, the former restrictions imply that the schooling level has to be measured when the

[9] Our "local" definition are equivalent to area, since the ECHP does not offer disaggregated information.

[10] These are the unique age span offered by the INE.

[11] In the next version of this paper will include the present value of average life-time earnings computed from the ECHP, making an out-of-sample-prediction

[12] The use of data obtained directly from the parents avoids the measurement errors provoked by the use of a cross-sectional response given by the children as a proxy for the background variables (Haveman and Wolfe (1995)).

[13] The use of one-year "window" measurement is pointed out by Haveman et al (1996) as a weak proxies for childhood circumstances and events. The ECPH is subject to the "window" problem, although we can construct some age-specific variables, as family structure measures.

individuals are aged 17-21. It corresponds to the typical age span in which those individuals willing to pursue post-compulsory level studies, do so (the highest frequency when individuals enroll in high school is 16-18 and college entry is 18-21. Hence, our study differs from previous Spanish researches since in these studies no longitudinal data set are available and therefore, the data only allowed to take measures of backgrounds variables in the same year as the educational outcomes.

The individuals aged 15-18 in 1994 are 1704. The former restrictions together with some incomplete information produce that 25,2 per cent of the sample were excluded. Firstly, we exclude 280 observations (6,3 per cent) for missing values about individual information. Moreover, 19 individuals (1,1 per cent) are also eliminated because their schooling records are seriously uncompleted and also confused. Furthermore, 36 individuals (2,1 per cent) who does not live in parental household are dropped. Finally, 79 individuals (4,6 per cent) are eliminated because since it is not available information about their parents records. The final sample is 1290 individuals.

4.1 Variables.

In this section, we describe explanatory and endogenous variables. Descriptive statistics of the variable are presented in Table 1.

4.1.1 Endogenous variable.

As we observe the outcome when individuals are 17-21 years old, a lot of children are still enrolled. The problem is that for children who are still enrolled, the current grade level does not necessarily represent their final grade attainment. Such observations are right-censored and could potentially bias the estimates of the school attainment model (Tansel (1998), Glick and Sahn (2000))[14]. Consequently, we use several measures of educational attainment in order to assess whether our findings are reasonable robust and consistent.

In the first one, we assume that the observed schooling level is the actual schooling level (NIVES). The problem associated with this approach is that some restrictive assumptions are imposed: i) dropouts are not considered, ii) the possibility of continuing from lower to higher degrees is not taken into account, iii) individuals who left school do not return[15]. For the former outcome measure, educational attainment of the children are grouped into five classes in ascending order[16]: primary school (no qualifications, first-stage of secondary and lower),

[14] The censoring problem can be eliminated by restricting the sample to older cohort, who has finished school, but we could not obtain the determinants at the time they are relevant (nearly sixteen).

[15] This assumption is quite realistic since as it is showed in Cameron and Heckman (1998) and Card (2001), people who leave school rarely return.

[16] In 1990 a new educational law (LOGSE) was aproved, but the implementation of the new program is gradual . By the year 2002, the new primary and secondary education have completely replaced by the previous one. The measures of educational attainment are obtained using the LOGSE.

middle vocational school, high school, upper vocational school and university degree.

The second approach (NIV) considers the final level attainment as that the level actually completed by individuals. A drawback of this approach is the determinants of enrolling at the university can not be accurately analyzed, because individuals are too young have received a degree yet. We consider three groups of educational attainment: primary school, lower vocational degrees and higher education (we include here people who finish higher vocational degrees and university degrees, because at the age we are analyzing the outcome it is rare to obtain these degrees).

Finally, in the last approach we focus on the level the individuals dropout educational system (DROPOUT) (see Chevalier and Lannot (2001)). We distinguish into four levels in ascending order: finish primary school, finish vocational degrees, finish high school and if they are still in school (we include in this group people who finish university). This approach relays on the fact that at the age group we analyze educational outcomes, the final grade of schooling and the decision of continuing studying are highly correlated and influenced by the same variables.

4.1.2 Individuals controls.

A set of dummies indicating the age of the children in December of 1994 are included to observe the cohort effects. Moreover, we construct a dummy indicating the gender and several regional dummies indicating gender differences and the area effects, respectively.

In some regressions, we minimize the potential biases provoked by the right censored data , by means of including further dummies which are constructed by interacting the former ages variables with an additional dummy, still in school.

4.1.3 Family background variables.

As we saw in Section 2, the family backgrounds when individuals grew up are likely to influence educational outcomes. For these reasons, young adults are matched with information about their mother (father)-figure. The mother (father)-figure is the natural or adoptive in the case the family remains intact, but will be a step-mother (father) in other cases[17]. For short, we shall refer to mother-figures as mother (father).

As the educational level of the parents is also likely to play a role, we generate a set of dummies for the level of education of the mother and the father, measured as the highest completed academic qualifications, and they are grouped into three classes in descendant order: degree qualifications, secondary school and no qualifications. These variables may affect children's educational outcomes through several path-ways: it may affect the taste for education (non

[17] This causes that the effect of several variables becomes weaker than we should expect. Furthermore, some observations must be dropped when we calculate some variables as parents' age at birth.

pecuniary effects), the quality of parenting'[18]. Moreover, it is also interesting to analyze how assortative mating of the parents affect educational outcomes of their children [Plug (2002)]. As it is shown in Table A3-5 in the Appendix, marital sorting for women in Spain strongly depends on schooling. We observe that about 70 per cent of woman are married with a partner with the same educational level. In contrast, only the 41 per cent of the parents with higher qualification are married with woman the same level of education. We include some interactions terms between mothers' education and fathers' education in order to capture these effects.

Financial situation of the family has revealed as determinant in schooling attainment (see Cameron and Heckman (1998a)). As a proxy of parental income we use the household income in 1993 [19]. We divide family income into four groups based on percentiles. Moreover, the ECPH contains information about parent economic situation, which may be used as an indicator of the probable permanent income during childhood as well as social status. For these reasons, a set of dummies variables have been constructed to describe the employment situation of the parents: "employment", "not employment" and "out of the labor force". Missing values are replaced for "out of the labor force".

4.1.4 Household composition.

Some economic and sociological research have recently devoted a lot of attention to the relevance of family structure in children's educational outcomes. The social science literature posits a great number of mechanisms relating family structure and children's outcomes [20]. Stress theory relies on the fact that family structure affects the break itself and not the break period. Social control focus on the fact that an intact family supervising and monitoring children better than in only-parent families. Finally, other authors focus in the fact that family income is lower in a only-parent family. Despite of this, there is no previous studies for the Spanish case tackling the relationship between education and family structure. We analyze this issue constructing several measures of family composition. Firstly, we generate a dummy indicating if the children live in a lone-parent family. Moreover, the literature indicates the relevance of the children's age when the household is broken (Bogess (1998)). For these reasons, we also distinguish between four child development stages[21]: 0-3, 4-10, 11-15 and +15[22], since the ECHP [23] allow us to observe the time on the start to live

[18] Hanuskeck (1992) and Feinstein and Symonx (1999) show that parents with higher education groups tend to spend more time with their children because they value education more than others parents.

[19] Information of a single year is a crude proxy for the financial situation of the child when growing up (see Wolfe et al (1996)), but it can be argued that this variable is more likely to be relevant when the individual is nearly sixteen.

[20] See Hill et all (2001), Ermisch and Francesconi (2001) and Manski et al (1994).

[21] We make this clasification on the basis of the distribution of this variable in the sample.

[22] If the child was born outside a live-in partnership, this variable takes zero value.

[23] The ECHP does not allow us to control for differential changes in family structure. We can only incorporate the last change. Althought this measure is far from being precise, it is better than to measure the family structure only one year.

in a lone parent family.

Ermisch and Francesconi (2001) show that the age in which mother and father gave birth are relevant. For these reasons, we generate continuous variables that pick up these effects. Following Ermish and Francesconi (2001) we generate dummy variables for the cases where the mother's (father's) age at birth was bellow or equal to 21 and greater or equal to 35.

Moreover, we also take into account the relationship between sib-ship structure and educational outcome (Iacovou (2001)). We compute the number of siblings and generate a dummy to indicate if the children are only child.

4.1.5 Labour market conditions.

We also include labour market conditions, in order to test the implications of the different models analyzed in section 2. In this sense, we assume that the expected return of post-compulsory education are strongly influenced by the conditions currently prevailing in the market for people who has similar characteristics [see Lauer (2001), that makes the same assumptions]. Some studies (Dominitz and Manski (1996) for the USA and Brunello (2001) provide evidence that students expectations do not deviate significatively from the observable wage structure. These effects are captured by including in the model some measures of unemployment rates.

In order to capture the mixed effects of unemployment in school attainment, we match individuals records with several unemployment measures. Since there exists a considerable variation in unemployment, we use a mean of unemployment prospects of 93-94 (see Tables A6-A10 in the Appendix). As a measure of the "opportunity cost" of participation in compulsory education, we focus on the unemployment rate among 16-24 years old. Following model proposed in section 2, we expect this variable to have a positive sign. Furthermore, we also use the unemployment rate of primary workers of the whole working age population as a measure of "opportunity cost". We expect that this variable has a positive effect, since it diminishes foregone earnings of education but also it increases the expected returns of education. In this sense, in order to observe the expected returns to education in a complete manner, we include the unemployment prospects of the whole university workers. We should expect a negative sign of this variable. It is important to note that it is not available the data of unemployment prospects by education levels only for adults. Consequently, this measure can be contaminated by young unemployment and we can obtain mixed effects. We must take into account this fact in the econometrics results. Finally, the unemployment rate of people aged 25-65 years old is used to measure the fact that unemployment rates reducing returns to education through diminishing all wages. This variable can also reflect the unemployment of different levels of education. For this reason, the expected sign is ambiguous As in the former case, these have to be taken into account when we interpret the results.

5 RESULTS.

5.1 Results of family backgrounds.

In this section, we show the estimates obtained using only individual controls, family background variables and family composition. This enables an understanding of the relationship between these variables and outcomes, abstracting from the effects of labour market conditions, which will be examined in the next section.

We specify four models for each outcome measure described in Section 3. In model I, we control by age, family structure, sex, income, regional controls and employment situation of the parents. In model II, our baseline model, we introduce mother and father's education. In model III, we additionally control whether mother's (father) age at birth is below 21 or greater to 35, if children are only child and the number of siblings. We also introduce some variables in order to observe (for lone parents families) the timing at which the household is broken. Finally, in model IV, we omit income and employment dummies of the parents as control. The results are presented in the tables 2, 3, 4 and 5, respectively. At the bottom of each table, we list the $p-value$ for the additional controls included in our regressions.

In Table 1, we present the results for the first outcome (NIVES). In model I, we observe that income has a strong impact in the educational attainment of children. The current unemployment and inactivity state of the parents affect negatively the outcome of the children, although the effects of the mother employment status are smaller. Furthermore, the effects of living in a broken household has a strong negatively effect in educational attainment. In model II, we introduce education of the parents. These variables are statistically significant and quantitatively important. It is important to note that this fact produces that the effect of income strongly downs and also affects parents employment status, although household income in 25th percentil remains significant. Surprisingly, father's completion college is more relevant than mother's completion, although mothers' secondary school is more important than father's. We will investigate these facts below. In model III, we try to observe if household composition it is also relevant. To assess the role of living in a one-parent family, we introduce variables measuring the timing at which child's family structure change. We can observe two important facts. Firstly, we find strong evidence that exists a negative relationship between children outcomes and early family disruption when child was aged 0-3. Furthermore, when the mother's age at birth's is lower or equal than 21, it is also relevant. The former findings may also suggest that the effect of single mother plays an important role. Finally, in model IV, we exclude family permanent income variables and we observe that the effects of mother's education and father's university degrees increase, revealing linkages between university degrees and income. A more interesting result is that the coefficients on the family structure are hardly affected. These results are consistent with Hill et all (2001). This fact provides evidence that the linkage between family structure and outcomes of the children does not depend

on financial opportunities.

If we consider the second endogenous variable, (NIV), we obtain similar results, (see Table 3). Firstly, when we control by education of the parents and family structure, income effects are less important, although it is observed that there exist difficulties for children from poorer families. This fact is reinforced by the fact that father out of work is negative and statistically significant. Furthermore, living in a lone parent family is associated with a significant lower educational attainment. Moreover, if we introduce several dummies to indicate the age at which the household is broken, we obtain the same results that in the former outcome: there exists an important negative association between schooling and experience in a single family when young adults was aged 0-3. Moreover, it is important to note that mother's completion of higher education plays a more important role than father's, although, in contrast with the previous outcome, the effects of both mother and father completion university degree have the same impact.

Finally, in Table 4, we use as outcome (NIVES) and interact age dummies with another variable, still in school. In this case, all former results remain.

Now, we analyze the main factors governing the decision of continuing studying (DROPOUT) (see Table 5). As we found in previous outcomes, parent's education are a strong predictor of this outcome. Moreover, we also observe that economic variables play a role, since the number of siblings and father's unemployment pattern are statistically significant. However, we observe that household income, together with variables of family structure are not relevant, in contrast with the former outcomes. These results are consistent with other studies that analyze children's dropout (e.g. Rice (1999) observes that family structure are not relevant on enrolment decision of young males using a sample of 16/17 years old in the years 1988, 1990 and 1991). Finally, it is important to note that regional controls are more important in the decision of continuing studying that in determining the level of school attainment.

Finally, it is also interesting to analyze the effects of parents' education. In Table 6 are shown additional models in order to distinguish by which mechanisms perform parental level of education and also to observe if the marital sorting by educational level is disturbing our results. In models I (II), III (IV), and V (VI) we perform the regressions using only mother's (father's) education for the three outcomes (NIVES, DROPOUT and NIV respectively) In models VII, VIII and IX we use interactions terms of parental education. At the bottom of the table, we list the *p-value* for the additional controls included in the different models. In models I-VI, we can observe that both coefficients and *t-statistics* are highly affected when we consider only mother's or father's education. These could be interpreted as evidence that assortative mating of parents is disturbing our results. Models VII and VIII show that interactions effects are strong predictors of children' educational choices.

Comparisons with another Spanish research findings are complicated by differences in specification. These differences include: sample construction, outcome measures, estimation techniques and different controls. However, we try to compare these findings with similar European and American works. We focus

both on the level of school attainment (NIV and NIVES) and in continuing studying (DROPOUT).

In conclusion, our findings are:

- Young adults from poorer families have lower educational attainments. This result is consistent with Ermish and Francesconi (2001) for England and also for a lot of American studies (see Haveman and Wolfe (1995)). Previous studies for the Spanish case (Gónzalez and Dávila (1997), Martinez (1999) find that income is a strong determinant, although it is one least important of a set of economics variables. The problem of these studies is that they are based on a sample of dependents, that can underestimate the effects of family income (see Cameron and Heckman (1998b) for a study of these questions). In contrast, household income are not significantly associated with the probability of continuing in school.

- There exists evidence that the current employment of the father affects negatively the outcome. Moreover, this effect is reinforced if the parent is currently out of work. These results are consistent with other American studies. The effect of the mother's employment pattern is more ambiguous. We obtain a negative and statistically significant relationship between mother's unemployment pattern and children outcomes, but there is little evidence that the mother being out of work affects children outcomes. The effects of mother's work on children's educational choices found for other research is mixed, suggesting a negative effect of the loss of the child care time.

- Educational levels of the parents appear as strong determinants of educational attainment, and also in the outcome still in school. Moreover, the result show that education of the mother is more relevant if the mother has secondary school (see Table 1,2, 4) and father's education is more relevant if he has a university degree. However, there exists some evidence (see Table 6) that marital sorting by schooling for mothers is disturbing our results.

- Several measures of family structure reveal themselves as very important in educational decisions, although we control for other family background variables. Other Spanish research, Albert (2000), Martinez (1999) do no find evidence of the relationship between living in a lone parent family and educational attainment. The difference is that they focus on analyzing the decision to enroll in the university and this must cause sample selection problems. However, in all the American studies that included information on family structure, growing up in a one-parent family is negatively related (see MacLanahan and Sandefur (1994) for reviews of past researches). Moreover, it is important to note that the effect of only parent structure is more relevant if the break is produced when children are 0-3 years old. Furthermore, when the mother's age at birth's is lower or equal that 21 is also relevant. They also might indicate a single mother effect. In contrast, we obtain that family structure does not affect dropout schooling.

5.2 Results of labour market conditions.

In this section, we test the effects of labour market conditions in the educational decision (see the model develop in section I). Our objetive is to capture the effect of unemployment in educational achievement and continuing schooling, but also to analyze through which ways unemployment affect the education outcomes of the children (i.e."opportunity cost" versus "expectative effect". Our empirical strategy is the following. Firstly, in model I, II, IV and VI, we observe the effect of each of measure of unemployment separately. Secondly, in models VIII and X, we consider two unemployment rates simultaneously, in order to distinguish more accurately the different effects of unemployment prospects on education. Finally, in model III, V, VII, IX and XI, we also introduce interactions effects between labour market conditions and gender dummies in order to capture differences between males and woman. Table 7 and 8 contain the former models for two outcomes: (NIVES) [24] and (NUEV). At the bottom of these tables (and the following tables), we list the *p-value* for the additional controls included in the different models.

In these tables, we observe that the effect of unemployment rate of university workers is not statistically significant and have a positive sign. This result should be interpreted with caution, since this measure is contaminated by the effect of young unemployment. In models VIII and X we profundize in this variable.

The coefficient of unemployment rates of no qualificated workers has the expected sign and is significant at standards levels. This coefficient can reflect the opportunity cost of education, but also the fact that greater unemployment rates of no qualificated worker increase the return to education. The results show that adults unemployment rates have a positive sign.

We can also observe that the effect of unemployment rates of youngsters is positive and larger than the other unemployment rates.

It is important to note that all interactions effects between unemployment rates and gender have a negative sign. This fact indicates that for woman, the effects of unemployments rates are smaller. Finally, we also observe that the effect of unemployment is stronger in the enrolment decision than in the level of school attainment.

These results are similar to Rice (1999), which observes a positive effect of unemployment rate on enrolment decision of young males. MacVicar and Rice (2001) and Pissarides (1981), provide the same evidence using time series data. According to the model of the first section, we can deduce that unemployment prospects affect schooling outcomes changing the cost of education, rather than returns to education.

In order to distinguish more properly the different effects of unemployment prospects on education, we consider two unemployment rates simultaneously. Firstly, we consider unemployment of university and primary workers in model VIII. This model allow us to contrast in a complete manner the "return effect of unemployment". In model X, we include unemployment of university degrees

[24] The results for the other outcome (NIV) are very similar to (NIVES). These results are available under request.

and young unemployment in order to isolate the effect of unemployment of university degrees of adults.

Firstly, we can observe in model VIII that unemployment of primary workers reinforce its effect in school attainment and enrolment decision, while unemployment rate of university degrees has not a significant impact. It is important to note that interaction effect between unemployment of primary workers and gender dummy are strong and negative, showing that the effect for woman are smaller than for men. However, model IX shows that unemployment rate of higher degree has a strong negative, since unemployment of young has a positive effect. This specification allows us to capture different effects of unemployment. These results are stronger when we consider the second measure of educational outcome: ($NUEV$).

These results are similar to Petrolongo and San Segundo (2000). In this paper, the authors showed, using a sample of individuals aged 16-17 in 1987, 1991 and 1996 that staying on school responds in fact positively to youth adult unemployment and negatively to adult unemployment. Moreover, Fernandez and Shioji (2000), using a panel data for 1983 to 1994 observe that unemployment of university degree has a negative effect, since unemployment has a positive effect.

6 CONCLUSION.

In this paper we analize the determinants of educational attainment and enrolment in post-compulsory education in Spain using a sample of data drawn for the first four waves of the EPHS. More specifically, we analyze the role played by family backgrounds and labor market conditions, with special attention to unemployment prospects.

Our results show that children education achievement is strongly related to parents education, although the presence of marital sorting by schooling (specially in the mothers) does not allow us to distinguish whether father's or mother's education play more important role. Youngsters from poor families find also difficulties in accessing higher levels of education. Moreover, family structure measures are relevant. Our results suggest that single mother's children have less probability to obtain higher education levels. With respect to the decision of continuing studying, the most relevant determinants are the region and the parental education. Unemployment prospects have also effects in children's educational outcomes, specifically in the decision of continuing in school. Moreover, our results suggest that unemployment prospects affect the demand for education through dimishing the cost more than increasing the returns to education.

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TABLE 1. DESCRIPTIVE STATISTICS.

Variable	Mean	Standard desviations	Range
Actual school level			
Primary school (no qualifications)	0.2825	0.4504	0-1
Middle vocational school	0.1842	0.3878	0-1
Higher education	0.1927	0.3946	0-1
Upper Vocational school	0.0565	0.2310	0-1
University degrees	0.2841	0.4504	0-1
Highest academic qualifications			
Primary school	0.4776	0.4997	0-1
Lower vocational degrees	0.1091	0.3119	0-1
Higher education	0.4118	0.4923	0-1
Drop-out school			
Drop-out when finish primary school	0.2686	0.4434	0-1
Drop-out when finish vocational degrees	0.0511	0.2203	0-1
Drop-out when finish high-school	0.1099	0.3129	0-1
Still in school	0.5704	0.4952	0-1
Individuals controls			
Age 15[a] (reference category)	0.2260	0.4184	0-1
Age 16	0.2345	0.4239	0-1
Age 17	0.2701	0.4442	0-1
Age 18	0.2693	0.4438	0-1
Woman	0.4737	0.4995	0-1
North-east1	0.1231	0.3286	0-1
North-east2	0.1680	0.3740	0-1
Madrid	0.1014	0.3020	0-1
Centre	0.1401	0.3472	0-1
East	0.1803	0.3846	0-1
South	0.2105	0.4078	0-1
Canarias	0.0759	0.2649	0-1
Family backgrounds			
Household income[b]	2,635,981	1,870,805	76.422-1,67*10^7
25th percentile	1,489,136		
50th percentile	2,163,244		
75th percentile	3,246,000		
Mother's education[c]			
No qualifications (reference category)	0.8124	0.3905	0-1
Secondary school	0.0950	0.2933	0-1
Degree qualifications	0.0926	0.2900	0-1
Father's education[d]			
No qualifications (reference category)	0.7226	0.4479	0-1
Secondary school	0.1223	0.3277	0-1
Degree qualifications	0.1551	0.3622	0-1
Mother's employment status (EPA)[*]			
employment (reference category)	0.3203	0.4668	0-1
not in employment	0.1264	0.3324	0-1
out of the labour force	0.5181	0.4999	0-1
Father's employment status(EPA)[**]			
employment (reference category)	0.7875	0.4092	0-1
not in employment	0.0987	0.2983	0-1
out of the labour force	0.1020	0.3028	0-1

Household composition			
Mother's age at birth*	28.1779	5.6377	16-45
less or equal than 21	0.0926	0.2900	0-1
more or equal than 35	0.1523	0.3594	0-1
Father's age at birth**	31.2160	6.3886	0-1
less or equal than 21	0.0902	0.2866	0-1
more or equal than 35	0.1526	0.3598	0-1
Number of siblings	1.7291	1.1706	0-8
Only child	0.0937	0.2915	0-1
Father-only	0.0820	0.2745	0-1
Mother-only	0.0139	0.1173	0-1
Child's age household is broken[k]			
Age 0-3	0.0108	0.1036	0-1
Age 4-10	0.0348	0.1834	0-1
Age 11-15	0.0294	0.1690	0-1
Age +16	0.0124	0.1106	0-1

[a]Age in 1994.

[c]Computed for individuals with available mother's information, Missing values are replaced with "no qualifications."

[d] Computed for individuals with available father's information, Missing values are replaced with "no qualifications".

*Computed for individuals with available mother's information. Missing values are replaced with reference cathegory.

**Computed for individuals with available father's information. Missing values are replaced with reference cathegory.

[k]Computed for individuals with available parent's information. Missing values are replaced with reference cathegory.

TABLE 2.
DETERMINANTS OF SCHOOL ATTAINMENT.
OUTCOME VARIABLE: NIVES

	Model I	Model II	Model III	Model IV
Age 15	0.181	0.193	0.217	0.217
	(2.15)	(2.24)	(2.49)	(2.51)
Age 16	0.198	0.264	0.274	0.29
	(2.39)	(3.12)	(3.22)	-3.45
Age 17	0.209	0.251	0.254	0.248
	(2.46)	(2.92)	(2.92)	(2.85)
Household income				
25th percentile	-0.615	-0.237	-0.246	
	(-5.9)	(-2.1)	(-2.12)	
50th percentile	-0.546	-0.199	-0.21	
	(-5.53)	(-1.88)	(-1.93)	
75th percentile	-0.375	-0.084	-0.087	
	(-3.83)	(-0.83)	(-0.85)	
Woman	0.366	0.392	0.402	0.41
	(5.96)	(6.3)	(6.45)	(6.58)
Father's employment status				
not in employment	-0.394	-0.31	-0.268	
	(-3.62)	(-2.8)	(-2.42)	
out of the labour force	-0.477	-0.385	-0.367	
	(-3.99)	(-3.18)	(-2.85)	
Mother's employment status				
not in employment	-0.177	-0.2	-0.188	
	(-1.59)	(-1.83)	(-1.71)	
out of the labour force	-0.135	-0.087	-0.053	
	(-1.74)	(-1.1)	(-0.66)	
Lone-parent family	-0.323	-0.215		
	(-2.68)	(-1.79)		
Mother's education				
Secondary school		0.396	0.376	0.431
		(3.46)	(3.22)	(3.68)
Degree qualifications		0.34	0.317	0.434
		(2.59)	(2.39)	(3.38)
Father's education				
Secondary school		0.242	0.225	0.285
		(2.23)	(2.05)	(2.59)
Degree qualifications		0.795	0.811	0.906
		(6.92)	(7.03)	(8.13)
Mother's age at birth less or equal 21			-0.259	-0.297
			(-2.09)	(-2.42)
Mother's age at birth more or equal 35			0.118	0.079
			(0.92)	(0.64)
Father's age at birth less or equal 21			-0.131	-0.139
			(-0.66)	(-0.69)
Father's age at birth more or equal 35			-0.132	-0.178
			(-1.34)	(-1.86)
Only Child			0.048	-0.101
			(-0.36)	(-0.79)
Number of siblings			0.121	-0.125
			(-4.01)	(-4.14)
Child's age household is broken[k]				
Age 0-3			-0.574	-0.521
			(-2.11)	(-1.96)
Age 4-10			-0.171	-0.131
			(-0.91)	(-0.74)
Age 11-15			-0.151	-0.129
			(-0.83)	(-0.74)
Age +15			-0.327	-0.294
			(-0.98)	(-0.88)
P-value: Regional Controls	0.106	0.224	0.333	0.084
Pseudo R^2	**0.047**	**0.072**	**0.079**	**0.072**
Number of observations	1290	1290	1290	1290

Note: T-statistics in brackets. They are computed using White's (1982) for heterocedasticity and cluster by family.

TABLE 3.
DETERMINANTS OF FINISH LEVEL OF ATTAINMENT.
OUTCOME VARIABLE: NIV.

	Model I	Model II	Model III	Model IV
Age 15	0.113	0.118	0.143	0.144
	(1.08)	(1.12)	(1.34)	(1.35)
Age 16	0.395	0.435	0.449	0.459
	(4.07)	(4.44)	(4.54)	(4.7)
Age 17	0.564	0.592	0.609	0.597
	(5.75)	(6.02)	(6.11)	(6)
Household income				
25th percentile	-0.418	-0.208	-0.205	
	(-3.74)	(-1.69)	(-1.65)	
50th percentile	-0.371	-0.175	-0.174	
	(-3.00)	(-1.46)	(-1.44)	
75th percentile	-0.187	-0.019	-0.009	
	(-1.75)	(-0.16)	(-0.08)	
Woman	0.317	0.317	0.323	0.333
	(-4.6)	(-4.55)	(-4.62)	(-4.77)
Father's employment status				
not in employment	-0.249	-0.206	-0.184	
	(-2.09)	(-1.74)	(-1.56)	
out of the labour force	-0.387	-0.344	-0.344	
	(-3.16)	(-2.82)	(-2.60)	
Mother's employment status				
not in employment	0.001	0.006	0.006	
	(0.01)	(0.05)	(0.05)	
out of the labour force	-0.163	-0.12	-0.098	
	(-1.94)	(-1.42)	(-1.12)	
Lone-parent family	-0.264	-0.223		
	(-2.15)	(-1.78)		
Mother's education				
Secondary school		0.292	0.271	0.327
		(2.22)	(2.05)	(2.52)
Degree qualifications		0.326	0.314	0.414
		(1.97)	(1.89)	(2.63)
Father's education				
Secondary school		0.019	0.008	0.07
		(0.16)	(0.07)	(0.6)
Degree qualifications		0.323	0.338	0.416
		(2.32)	(2.43)	(3.13)
Mother's age at birth less or equal 21			-0.155	-0.19
			(-1.15)	(-1.41)
Mother's age at birth more or equal 35			0.106	0.059
			(0.81)	(0.47)
Father's age at birth less or equal 21			-0.016	0.001
			(-0.07)	(0.01)
Father's age at birth more or equal 35			-0.066	-0.123
			(-0.65)	(-1.23)
Only Child			-0.089	-0.147
			(-0.65)	(-1.07)
Number of siblings			-0.103	-0.11
			(-3.00)	(-3.19)
Child's age household is broken[k]				
Age 0-3			-0.798	-0.73
			(-2.46)	(-2.31)
Age 4-10			-0.226	-0.182
			(-1.12)	(-0.92)
Age 11-15			-0.004	0.05
			(-0.02)	(0.27)
Age +15			-0.363	-0.329
			(-1.11)	(-1.01)
P-value: Regional Controls	0.054	0.085	0.142	0.04
Pseudo R^2	**0.055**	**0.065**	**0.071**	**0.064**
Number of observations	1290	1290	1290	1290

Note: T-statistics in brackets. They are computed using White's (1982) for heterocedasticity and cluster by family.

TABLE 4.
DETERMINANTS OF SCHOOL ATTAINMENT.
OUTCOME VARIABLE: NIVES

	Model I	Model II	Model III	Model IV
Age 15*still in school	1.099	1.007	1.224	1.011
	(12.59)	(11.09)	(9.32)	(11.22)
Age 16*still in school	1.277	1.262	1.683	1.274
	(14.46)	(14.13)	(13.24)	(14.36)
Age 17*still in school	1.449	1.389	1.492	1.378
	(13.54)	(12.86)	(10.88)	(12.71)
Household income				
25th percentile	-0.514	-0.231	-0.267	
	(-4.89)	(-2.00)	(-2.27)	
50th percentile	-0.479	-0.217	-0.283	
	(-4.88)	(-2.01)	(-2.53)	
75th percentile	-0.319	-0.099	-0.155	
	(-3.22)	(-0.96)	(-1.49)	
Woman	0.281	0.304	0.274	0.317
	(4.41)	(4.75)	(4.22)	(4.94)
Father's employment status				
not in employment	-0.304	-0.244	-0.239	
	(-2.79)	(-2.21)	(-2.10)	
out of the labour force	-0.393	-0.326	-0.276	
	(-3.41)	(-2.72)	(-2.10)	
Mother's employment status				
not in employment	-0.233	-0.238	-0.206	
	(-2.21)	(-2.25)	(-1.88)	
out of the labour force	-0.186	-0.147	-0.136	
	(-2.38)	(-1.86)	(-1.67)	
Lone-parent family	-0.284	-0.207		
	(-2.39)	(-1.73)		
Mother's education		0.282	0.235	0.33
Secondary school		(2.33)	(1.91)	(2.67)
		0.277	0.218	0.404
Degree qualifications		(2.08)	(1.65)	(3.16)
Father's education				
Secondary school		0.129	0.089	0.164
		(1.18)	(0.79)	(1.47)
Degree qualifications		0.633	0.574	0.723
		(5.5)	(4.95)	(6.46)
Mother's age at birth less or equal 21			-0.259	-0.31
			(-2.01)	(-2.45)
Mother's age at birth more or equal 35			0.135	0.078
			(-1.09)	(-0.65)
Father's age at birth less or equal 21			-0.121	-0.128
			(-0.52)	(-0.56)
Father's age at birth more or equal 35			-0.132	-0.149
			(-1.35)	(-1.59)
Only Child			-0.057	-0.159
			(-0.41)	(-1.20)
Number of siblings			-0.086	-0.108
			(-2.90)	(-3.67)
Child's age household is broken[k]				
Age 0-3			-0.663	-0.574
			(-2.70)	(-2.46)
Age 4-10			-0.143	-0.094
			(-0.74)	(-0.51)
Age 11-15			-0.16	-0.085
			(-0.88)	(-0.51)
Age +15			-0.371	-0.402
			(-1.32)	(-1.43)
P-value: Regional Controls	0.752	0.823	0.946	0.770
Pseudo R^2	**0.141**	**0.155**	**0.172**	**0.154**
Number of observations	1290	1290	1290	1290

Note: T-statistics in brackets. They are computed in the same way that Table 2.

TABLE 5.
DETERMINANTS OF DROPOUT SCHOOL.
OUTCOME VARIABLE: DROPOUT.

	Model I	Model II	Model III	Model IV
Age 15	-0.121	-0.106	-0.094	-0.089
	(-1.16)	(-0.98)	(-0.87)	(-0.83)
Age 16	-0.17	-0.124	-0.128	-0.113
	(-1.68)	(-1.19)	(-1.21)	(-1.08)
Age 17	-0.337	-0.322	-0.337	-0.335
	(-3.45)	(-3.21)	(-3.34)	(-3.32)
Household income				
25th percentile	-0.537	-0.122	-0.162	
	(-4.78)	(-1.00)	(-1.29)	
50th percentile	-0.433	-0.052	-0.088	
	(-3.99)	(-0.45)	(-0.75)	
75th percentile	-0.17	0.144	0.131	
	(-1.60)	(1.28)	(1.16)	
Woman	0.439	0.467	0.477	0.492
	(6.33)	(6.59)	(6.7)	(6.94)
Father's employment status				
not in employment	-0.359	-0.276	-0.237	
	(-3.01)	(-2.28)	(-1.95)	
out of the labour force	-0.511	-0.403	-0.375	
	(-4.21)	(-3.37)	(-2.93)	
Mother's employment status				
not in employment	-0.181	-0.209	-0.192	
	(-1.56)	(-1.77)	(-1.61)	
out of the labour force	-0.049	0.015	0.062	
	(-0.59)	(0.17)	(0.71)	
Lone-parent family	-0.273	-0.152		
	(-2.17)	(-1.18)		
Mother's education				
Secondary school		0.374	0.328	0.362
		(2.71)	(2.34)	(2.59)
Degree qualifications		0.458	0.413	0.442
		(2.77)	(2.43)	(2.7)
Father's education				
Secondary school		0.366	0.348	0.404
		(2.84)	(2.68)	(3.11)
Degree qualifications		0.944	0.965	1.021
		(6.39)	(6.4)	(7.01)
Mother's age at birth less or equal 21			-0.116	-0.164
			(-0.83)	(-1.19)
Mother's age at birth more or equal 35			0.033	-0.007
			(-0.24)	(-0.06)
Father's age at birth less or equal 21			-0.012	-0.018
			(-0.05)	(-0.07)
Father's age at birth more or equal 35			-0.078	-0.113
			(-0.71)	(-1.07)
Only Child			0.041	-0.018
			(-0.28)	(-0.13)
Number of siblings			-0.13	-0.128
			(-3.69)	(-3.59)
Child's age household is broken[k]				
Age 0-3			-0.226	-0.23
			(-0.59)	(-0.60)
Age 4-10			-0.097	-0.104
			(-0.49)	(-0.56)
Age 11-15			-0.181	-0.245
			(-0.85)	(-1.21)
Age +15			-0.153	-0.148
			(-0.42)	(-0.42)
P-value: Regional Controls	0.002	0.004	0.006	0.000
Pseudo R^2	**0.063**	**0.095**	**0.103**	**0.092**
Number of observations	1290	1290	1290	1290

Note: Standard errors are computed using White's (1982) for heterocedasticity
and also to take into account for observations of the same family.

TABLE 6.
ESTIMATES OF THE EFFECTS OF MOTHER'S AND FATHER'S SCHOOLING ON CHILDREN'S EDUCATIONAL OUTCOMES.

	Model I (nives)	Model II (nives)	Model III (dropout)	Model IV (dropout)	Model V (niv)	Model VI (niv)
Mother's education						
Secondary school	0.523		0.500		0.354	
	(4.55)		(3.67)		(2.82)	
Degree qualifications	0.689		0.795		0.496	
	(5.49)		(4.99)		(3.22)	
Father's education						
Secondary school		0.314		0.432		0.092
		(2.9)		(3.38)		(2.82)
Degree qualifications		0.967		1.141		0.488
		(8.92)		(8.08)		(3.78)
P-value: Regional Controls.	0.014	0.014	0.000	0.000	0.116	0.112
P-value: Age and sex controls.	0.000	0.000	0.000	0.000	0.000	0.000
P-value: Family backgrounds	0.000	0.000	0.000	0.000	0.000	0.000
P-R^2	0.057	0.068	0.076	0.092	0.061	0.061
Number of observations	1290	1290	1290	1290	1290	1290

	Model VII (nives)	Model VIII (dropout)	Model IX (niv)
Mother secondary school x	0.572	0.677	0.408
father secondary school	(2.56)	(2.35)	(1.63)
Mother secondary school x	1.058	1.172	0.441
father degree qualifications	(4.94)	(3.87)	(1.97)
Mother degree qualificationsx	0.527	0.385	0.169
father secondary school	(1.92)	(1.21)	(0.55)
Mother degree qualificationsx.	0.925	1.259	0.763
father degree qualifications	(5.88)	(5.52)	(4.37)
P-value: Regional Controls.	0.123	0.001	0.116
P-value: Age and sex controls.	0.000	0.000	0.000
P-value: Family backgrounds	0.000	0.000	0.000
P-R^2	0.061	0.082	0.063

Note: t-statistics in brackets. They are robust in the same sense that Table 2-5. Family backgrounds controls include the following dummies employment situation of the mother's (father's) , lone parent family and income. Moreover, we include number of siblings. Sex controls include woman and interactions between age and gender.

TABLE 7.
EFFECTS OF LABOR MARKET CONDITIONS IN THE LEVEL OF SCHOOL ATTAINMENT. OUTCOME: NIVES

	Model I	Model II	Model III	Model IV	Model V	Model VI	Model VII
Ln unemployment rates of university degrees	0.151						
	(0.31)						
Ln unemployment rates of primary workers		**0.378**	0.361				
		(1.6)	(1.53)				
Ln unemployment rates of primary workers X woman			**-0.36**				
			(-1.70)				
Ln unemployment rates of adults (25-65)				**0.679**	**0.627**		
				(1.84)	(1.69)		
Ln unemployment rates of adults (25-65) X woman					-0.480		
					(-1.67)		
Ln unemployment rates of young (16-25)						1.293	**1.484**
						(1.48)	**(1.67)**
Ln unemployment rates of young (16-25) X woman							-0.689
							(-1.24)
P-value: Regional Controls	0.305	0.213	0.266	0.133	0.198	0.174	0.161
P-value: Age controls	0.005	0.005	0.004	0.005	0.004	0.005	0.005
P-value: Family backgrounds	0.000	0.000	0.000	0.000	0.000	0.000	0.000
P-value: sex controls	0.000	0.000	0.000	0.226	0.239	0.312	0.398
P-R^2	0.076	0.077	0.078	0.077	0.078	0.077	0.077
Number of observations	1290	1290	1290	1290	1290	1290	1290

	Model VII	Model VIII	Model IX	Model X
Ln unemployment rates of university degrees	0.594	0.745	-1.114	-0.968
	(1.08)	(1.02)	(1.141)	(-0.87)
Ln unemployment rates of primary workers	**0.505**	**0.443**		
	(1.89)	**(1.65)**		
Ln unemployment rates of univeristy degrees X woman		-0.289		
		(-0.58)		
Ln unemployment rates of primary workers X woman		-0.319		-0.452
		(-1.49)		(-0.66)
Ln unemployment rates of young (16-25)			**2.853**	**2.701**
			(2.01)	**(1.76)**
Ln unemployment rates of young (16-25) X woman				0.073
				(0.120)
P-value: Regional Controls	0.152	0.230	0.101	0.140
P-value: Age controls	0.005	0.004	0.004	0.004
P-value: Family backgrounds	0.000	0.000	0.000	0.000
P-value: sex controls	0.000	0.000	0.121	0.300
P-R^2	0.077	0.078	0.077	0.077
Number of observations	1290	1290	1290	1290

Note: t-statistics in brackets. They are robust in the same sense that Table 2-5. Family backgrounds controls include the following dummies of mother's (father's) education, employment situation of the mother's (father's) , lone parent family and income. Moreover, we include number of siblings. Sex controls include woman .

TABLE 8.
EFFECTS OF LABOR MARKET CONDITIONS IN DROPOUT SCHOOL.
OUTCOME: DROPOUT

	Model I	Model II	Model III	Model IV	Model V	Model VI	Model VII
Ln unemployment rates of university degrees	-0.103						
	(-0.19)						
Ln unemployment rates of primary workers		**0.609**	**0.585**				
		(2.22)	(2.11)				
Ln unemployment rates of primary workers X woman			**-0.567**				
			(-2.37)				
Ln unemployment rates of adults (25-65)				**1.009**	**0.908**		
				(2.37)	**(2.12)**		
Ln unemployment rates of adults (25-65) X woman					-0.741		
					(-1.90)		
Ln unemployment rates of young (16-25)						1.493	**1.730**
						(-1.53)	**(1.76)**
Ln unemployment rates of young (16-25) X woman							-1.052
							(-1.66)
P-value: Regional Controls	0.036	0.002	0.005	0.002	0.011	0.005	0.006
P-value: Age controls	0.005	0.005	0.064	0.006	0.006	0.006	0.007
P-value: Family backgrounds	0.000	0.000	0.000	0.000	0.000	0.000	0.000
P-value: sex controls	0.153	0.060	0.113	0.337	0.067	0.455	0.230
P-R^2	0.103	0.104	0.106	0.105	0.106	0.103	0.104
Number of observations	129	1290	1290	1290	1290	1290	1290

	Model VII	Model IX	Model X	Model XI
Ln unemployment rates of university degrees	0.455	0.525	**-2.104**	**-2.124**
	(0.77)	(0.64)	(-2.32)	(-1.56)
Ln unemployment rates of primary workers	**0.701**	**0.616**		
	(2.30)	(1.97)		
Ln unemployment rates of univeristy degrees X woman		-0.276		0.252
		(-0.470)		(0.34)
Ln unemployment rates of primary workers X woman		**-0.531**		
		(2,16)		
Ln unemployment rates of young (16-25)			**4.417**	**4.335**
			(2,74)	(2.37)
Ln unemployment rates of young (16-25) X woman				-0.576
				(-0.69)
P-value: Regional Controls	0.007	0.022	0.002	0.004
P-value: Age controls	0.036	0.005	0.005	0.005
P-value: Family backgrounds	0.000	0.000	0.000	0.000
P-value: sex controls	0.153	0.060	0.017	0.312
P-R^2	0.102	0.104	0.106	0.106
Number of observations	1290	1290	1290	1290

Note: t-statistics in brackets. They are robust in the same sense that Table 2-5. Family backgrounds controls include the following dummies of mother's (father's) education, employment situation of the mother's (father's) , lone parent family and income. Moreover, we include number of siblings. Sex controls include woman.

APPENDIX

TABLE A1: NUMBER OF DEPENDENTS BY AGE. 15-25

	Non dependent	Dependent	Total
15	3	371	374
%	*0.80*	*99.20*	*100*
16	5	387	392
%	*1.28*	*98.72*	*100*
17	12	426	438
%	*2.74*	*97.26*	*100*
18	9	412	421
%	*2.14*	*97.86*	*100*
19	25	378	403
%	*6.20*	*93.80*	*100*
20	19	414	433
%	*4.39*	*95.61*	*100*
21	42	329	371
%	*11.32*	*88.68*	*100*
22	46	354	400
%	*11.50*	*88.50*	*100*
23	87	316	403
%	*21.59*	*78.41*	*100*
24	72	305	377
%	*19.10*	*80.90*	*100*
25	102	243	345
%	*29.57*	*70.43*	*100*
Total	422	3,935	4357
	9.69	*90.31*	*100*

Note: Missing values are assumed to be dependent.

TABLE A2: MEAN INDIVIDUALS THAT LIVE AT HOME. 15-18 YEARS OLD.

	Obs	Mean	Std. Dev.
Dependent	1.625	0.982	0

TABLE A3: MARITAL SORTING BY SPANISH ADULTS BY EDUCATIONAL LEVELS.
(number of observations).

	Father's Degree qualifications	Father's Secundary school	Father's no qualifications	Total
Mother Degree qualifications	74	18	16	108
Mother's Secondary school	36	27	43	106
Mother's no qualification	71	100	783	954
Total	**181**	**145**	**842**	**1168**

TABLE A4: FATHER'S MARITAL SORTING BY EDUCATIONAL LEVELS. (%)

.	Father's Degree qualifications	Father's Secundary school	Father's no qualifications
Mother Degree qualifications	40.88	12.41	1.90
Mother's Secondary school	19.89	18.62	5.11
Mother's no qualification	39.23	68.97	92.99
Total	100.00	100.00	100.00

TABLE A5: MOTHER'S MARITAL SORTING BY EDUCATIONAL LEVELS. (%)

.	Mother Degree qualifications	Mother's Secondary school	Mother's no qualification
Father's Degree qualifications	68.52	33.96	7.44
Father's Secundary school	16.67	25.47	10.48
Father's no qualifications	14.81	40.57	82.08
Total	100.00	100.00	100.00

TABLE A6: UNEMPLOYMENT RATES BY LEVEL OF EDUCATION, SEX AND REGION. 1993*

	Pestph	Pestpm	Pestuh	Pestum
Norest1	0.128	0.135	0.095	0.201
Norest2	0.101	0.237	0.100	0.188
Madrid	0.140	0.187	0.088	0.186
Centre	0.164	0.281	0.092	0.206
East	0.163	0.256	0.090	0.134
South	0.299	0.334	0.113	0.222
Canarias	0.277	0.365	0.070	0.143

TABLE A8: UNEMPLOYMENT RATES BY LEVEL OF EDUCATION, SEX AND REGION. 1994*

	Pestph	Pestpm	Pestuh	Pestum
Norest1	0.152	0.148	0.096	0.244
Norest2	0.074	0.183	0.101	0.166
Madrid	0.174	0.307	0.112	0.196
Centre	0.176	0.293	0.088	0.254
East	0.168	0.275	0.085	0.170
South	0.303	0.393	0.120	0.247
Canarias	0.277	0.337	0.083	0.161

TABLE A9: UNEMPLOYMENT RATES BY AGE , SEX AND REGION. 1993.

	Pme25h	Pme25m	Pma25h	Pma25m
Norest1	0.368	0.5531	0.129	0.187
Norest2	0.399	0.4878	0.109	0.244
Madrid	0.311	0.3927	0.119	0.196
Centre	0.364	0.4978	0.131	0.271
East	0.371	0.4221	0.131	0.219
South	0.500	0.5516	0.232	0.317
Canarias	0.429	0.5428	0.199	0.295

TABLE A10: UNEMPLOYMENT RATES BY AGE , SEX AND REGION. 1994.

	Pme25h	Pme25m	Pma25h	Pma25m
Norest1	0.401	0.506	0.141	0.208
Norest2	0.407	0.517	0.118	0.258
Madrid	0.387	0.423	0.142	0.223
Centre	0.358	0.512	0.138	0.292
East	0.375	0.449	0.138	0.244
South	0.493	0.599	0.237	0.354
Canarias	0.440	0.509	0.190	0.255