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Earnings Risk and Demand for Higher Education: A Cross-Section Test for Spain

Joop Hartog & Luis Diaz-Serrano

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EARNINGS RISK AND DEMAND FOR HIGHER EDUCATION: A CROSS-SECTION TEST FOR SPAIN

JOOP HARTOG

FEB-Scholar, Universiteit van Amsterdam

LUIS DIAZ-SERRANO*

Universitat Rovira i Virgili, CREB and IZA

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We develop a simple human capital model for optimum schooling length when earnings are stochastic, and highlight the pivotal role of risk attitudes and the schooling gradient of earnings risk. We use Spanish data to document the gradient and to estimate individual response to earnings risk in deciding on attending university education, by measuring risk as the residual variance in regional earnings functions. We find that the basic response is negative but that in households with lower risk aversion, the response will be dampened substantially and may even be reversed to positive.

JEL classification codes: I21

Key words: earnings risk, schooling decisions

I. Introduction

There can be no doubt that schooling is a risky investment. An individual deciding on schooling is at best imperfectly aware of her abilities, the demands of the school curriculum, the probability to succeed, the nature of the job that may be obtained after completing an education and the position within the post-school earnings distribution that may be attained. Neither can there be any doubt that the

* Luis Diaz-Serrano: Department of Economics, Faculty of Economics & Management, Universitat Rovira i Virgili, Av. de la Universitat 1, 43204 Reus (Spain); e-mail: luis.diaz70@gmail.com. Joop Hartog: Department of Economics, Faculty of Economics and Econometrics, Universiteit van Amsterdam, Roetersstraat 11, 1018 WB Amsterdam (The Netherlands); e-mail: J.Hartog@uva.nl. Comments by the two anonymous referees and the co-editor (Mariana Conte Grand) of this journal are gratefully acknowledged.

relation of these uncertainties with schooling decisions and outcomes is under-researched, although recently this literature seems to be taking off.

The literature is dominated by theoretical analyses and shortage of empirical work. The theoretical literature has started with Levhari and Weiss (1974).[1] They introduce a two-period model, with work in period 2 and a choice between time devoted to school and to work in period 1. The pay-off to school time is uncertain, but revealed at the beginning of period 2. Increasing risk (increasing variance in the pay-off to school time) reduces investment in education if good states of the world generate higher marginal returns to education.

Williams (1979) extends the theory by applying a stochastic dynamic programming model to education decisions, and linking it up with the finance literature on marketable investment. The production of human capital, the depreciation of human capital and future wages are all stochastic. Again, higher risk, as larger variance in the production of human capital from given inputs, reduces investment in schooling, unless risk aversion is very strong and the covariance between depreciation and production of human capital is highly negative. Hogan and Walker (2001) also construct a stochastic dynamic programming model, where being in school has utility value, and the shadow wage, to be realised when leaving school, follows a Brownian motion. Once the student leaves school, this shadow wage becomes the fixed wage for the entire working life. Increasing risk in the post-school wage implies an increase in the upside risk, the probability to obtain a high wage, while the increase in downside risk remains ineffective, because at a low wage students stay in school anyway. As a result, individuals react by staying in school longer as risk increases. Belzil and Hansen (2004) estimate a stochastic dynamic programming model on data from the NLSY 1979-1990. They conclude from their estimates that an increase in risk (variance of labour earnings) increases schooling length. This happens because increased risk in the labour market makes schooling more attractive as this comes with receiving more riskless parental income support.

The theoretical models generate different conclusions: increased risk may increase or decrease the length of schooling. One might assess these different outcomes by assessing the a priori plausibility of the models. Staying in school longer to benefit more from riskless parental transfers if variability in wages increases

[1] The analyses of Eaton and Rosen (1980), Kodde (1986) and Jacobs (2002) are applications and extensions.

is a priori not very convincing. In Hogan and Walker's model, the post-school market wage moves stochastically as long as the individual stays in school and is frozen as soon as the individual leaves school. This would seem most compatible with uncertainty about the amount of human capital produced while in school. If we then assume that the risk of human capital production is greater for less able individuals, the model would imply that less able individuals stay in school longer, hoping for a favourable draw. Again, this is a priori not very plausible.

However, the ultimate test of different predictions should be their empirical validity, and we will focus on an empirical analysis. As our frame of analysis we have developed probably the simplest model possible to analyse the effect of stochastic post-school earnings on the desired length of schooling, showing the key role of essential risk parameters and risk attitudes. We will then estimate the sensitivity of schooling decisions to variance in post-school earnings, by including regional observations on residual earnings variance in a probit for the decision to attend university education in Spain. The results show a negative effect of risk on investment, dampened by increasing taste for risk.

As our empirical strategy rests on assumptions that easily generate some controversy, we will discuss them up front. We assume that individuals base their schooling decisions on the structure of earnings they observe in their immediate environment among working individuals in their residential region (Comunidad Autónoma), using Spanish regions as the information units. We estimate earnings functions of individuals with given education in each region and use predicted earnings for different educations to assess expected returns and the residual variances as an indication for the risk associated with an education. Cochrane (2001) points out that in a lifetime welfare maximising framework the variance as such is not relevant, but the covariance of an asset with consumption is essential. We still denote the residual variance of wages as risk, as we abstract from optimal consumption profiles over the life cycle.[2] Restricting the information set to the region of residence no doubt is too limited for some individuals, but, as we argue

[2] For a pessimistic view on the possibilities to reduce the risk of education by financial investments, see Davis and Willen (2000) and Shaw (1996); on the relation between human capital risk and financial investment in a lifecycle consumption framework, see Palacios-Huerta (2003). He finds that at the aggregate level, the mean-variance frontier does not improve if returns from financial assets are added to returns from human capital, whereas in the converse case (adding human capital to financial assets) the frontier does improve. For separate demographic groups, the results vary by level of education.

below, seems quite acceptable to us in the Spanish context. Our key assumption is that potential students base their decisions on what they observe in the market at the time they have to make their decisions. Empirically, we know very little on the information set of individuals and on the formation of expectations. Dominitz and Manski (1996) elicit student expectations on earnings variances after different potential educations and find that expected variances are certainly not smaller than actually observed variances, thus not providing immediate support to the notion that observed variance overestimates perceived risk because it is biased by unobserved individual heterogeneity. In fact, the authors conclude that respondents have considerable uncertainty on their future earnings. Webbink and Hartog (2004) find that students can predict differences in mean earnings between university educations reasonably well but they cannot predict their own position within the post-schooling earnings distribution (the correlation between starting salaries as predicted by university freshmen and their realisations four years later, for the same individual, is 0.06).

As an alternative to our approach, one might use longitudinal data to deduce the information that individuals must have had when they made their schooling decisions, by constructing variances corrected for individuals' choices: ex post variance is corrected for selectivity to deduce ex ante uncertainty (cf. Chen 2005, Cunha et al. 2005). Indeed Chen (2005) uses a longitudinal dataset (NLSY1979) and then estimates residual variances in potential wages for four levels of education, distinguishing permanent and temporary components of the variances, and allowing for selectivity in the choice of schooling level. She defines uncertainty as the permanent component of variance in potential wage (by education) conditional on observables explaining schooling choice and unobservables in potential wages. Her results show that uncertainty (rather than heterogeneity) counts for most of the variance in potential wages. However, the marginal uncertainties from additional schooling levels are different from the marginal residual variances from additional schooling. She also finds significant correlation between the residual in schooling choice and in potential wage, supporting the relevance of unobserved heterogeneity. Clearly, Chen's model has uncovered very interesting information, and our basic approach is much simpler. The key difference between her and our approach is in the assumptions on the information that individuals use when taking their schooling decisions. We believe that using the earnings structure among cohorts already in the labour market represents better how individuals collect their information. We certainly would like to condition the outcomes for earlier cohorts on ability, test scores, school grades, etc., and apply this more precise information relating it to potential students' abilities and test scores. But we simply have no observations on such variables. We also agree that to measure true uncertainty associated with an education one should account for truncation from potential to observed wages and for unobserved heterogeneity. But it's another question whether students use this true uncertainty when making their schooling decisions or use the crude uncorrected residual variance, as we assume in this paper. We believe that individuals are poorly informed even on their own true ability to succeed in the labour market. Such information will gradually be built up during a school career and may very well differ between a highly competitive and selective school system such as the US has and the often less competitive systems in Europe. That's why we are engaged in research to collect data on the actual earnings expectations that students hold. With proper data, we can then condition expectations on individuals' qualities, thus turning at least some unobserved heterogeneity into observed heterogeneity. In the present paper, we acknowledge the potential role of unobserved heterogeneity in Section III.D, where we consider the sensitivity of our conclusions to assumptions on the endogeneity of returns and variances.[3]

II. A simple schooling model with uncertain returns

Suppose an individual faces potential earnings, depending on realized schooling *s*, in a simple multiplicative stochastic specification:

$$Y_{st} = \theta_{st} Y_s \,, \tag{1}$$

where Y_{st} is earnings at age t for given schooling length s, Y_s is a non-stochastic

[3] Recently, Cunha et al (2005) deduced from realised schooling choices and observed earnings that forecastable variability must have been a large portion of observed ex post variability. If this also holds for Spain, we would substantially overestimate risk. Still, Cunha et al.'s results on estimated forecastability are based on the model structure they impose. Directly asking students what information they use may give a different answer.

shift parameter and θ_{st} is a stochastic variable.[4] For a start, simplify to $\theta_{st} = \theta_s$ and let

$$E(\theta_s) = 1; \\ E\{\theta_s - E(\theta_s)\}^2 = \sigma_s^2. \tag{2}$$

θ_s is a stochastic shock around Y_s, with a single lifetime realisation, but with variance dependent on schooling length s.[5] This simple specification is similar in spirit to Levhari and Weiss's two period model, with a wage unknown when deciding on schooling, but with a single lifetime realisation (one wage rate for the entire post-school period).[6] We assume individuals cannot insure this risk and write the individual objective as maximum expected lifetime utility from income, discounted at rate ρ. Note that we ignore here, for simplicity, that individuals generally will care about consumption rather than income and hence will assess earnings uncertainty in terms of consumption uncertainty (see, e.g. ,Cochrane 2001, p. 15-16):

$$W = E\int_s^\infty U\{\theta_s Y_s\}e^{-\rho t}\,dt = \frac{1}{\rho}e^{-\rho s}\,E\left[U(\theta_s Y_s)\right]. \tag{3}$$

Apply a second-order Taylor series expansion around Y_s and write

$$E\left[U(\theta_s Y_s)\right] = E\left[U(Y_s)\right] + Y_s U'(Y_s)E(\theta_s - 1) + \frac{1}{2}Y_s^2 U''(Y_s)E(\theta_s - 1)^2 = \tag{4}$$

$$= U(Y_s) + \frac{1}{2}Y_s^2 U''(Y_s)\sigma_s^2.$$

Then, rewrite the objective function as

$$\max_s W(s) = \frac{1}{\rho}e^{-\rho s}\left[U(Y_s) + \frac{1}{2}Y_s^2 U''(Y_s)\sigma_s^2\right]. \tag{5}$$

[4] We might specify earnings at age t for schooling s as Y_{t-s}, $t \geq s$, reflecting dependence on experience rather than age. However, since we assume $Y_{st} = Y_s$, i.e. constant wages over experience, this is immaterial.

[5] A generalisation of the model, with uncorrelated annual earnings shocks, yields essentially the same conclusions. We refer to our IZA Discussion Paper for details, Hartog and Diaz-Serrano (2002).

[6] The specification is also backed up by some empirical evidence. For example, Baker and Solon (2003) find, in a long panel for Canada, that permanent shocks account for about two thirds of the inequality in annual earnings.

Setting the derivative with respect to *s* equal to zero, ignoring a term with $U'''(Y_s)$ and rewriting a little yields as optimum condition:

$$\varepsilon_s \left\{ \mu_s - \alpha_s \sigma_s^2 \left(\mu_s + \gamma_s - \frac{1}{2} \rho \right) \right\} - \rho = 0, \tag{6}$$

with

$$\mu_s = \frac{\partial Y_s}{\partial s} \frac{1}{Y_s} \geq 0\,; \tag{7}$$

$$\gamma_s = \frac{\partial \sigma_s}{\partial s} \frac{1}{\sigma_s}\,; \tag{8}$$

$$\alpha_s = \frac{U''(Y_s)}{-U'(Y_s)} Y_s\,; \tag{9}$$

$$\varepsilon_s = \frac{\partial U}{\partial Y_s} \frac{Y_s}{U(Y_s)} > 0. \tag{10}$$

Hence, μ_s is the marginal rate of return to schooling, γ_s is the relative gradient of risk to schooling, α_s is relative risk aversion and ε_s is the income elasticity of utility. The model is easily recognised as a generalisation of the Becker-Mincer model, which in a world without risk predicts investment up to the point where discount rate and marginal rate of return are equal (to see this, set $\sigma_s^2 = \frac{\partial \sigma_s}{\partial s} = 0$ and $\varepsilon_s = 1$). The second-order condition for an optimum requires the left-hand side of equation (6) to be a downward sloping function of *s*, which we assume to hold.

Effects of risk on demand for education length depend crucially on risk attitude α_s and on the term in the inner brackets. If this term is positive $(\mu_s + \gamma_s > (1/2)\rho)$, an increase in risk, at a constant risk gradient, will reduce optimum schooling for risk averters $(\alpha_s > 0)$ and increase it for risk lovers. However, if risk strongly falls with education $(\gamma_s < (1/2)\rho - \mu_s)$ the conclusion is reversed. An increase in the risk gradient reduces optimum schooling length for risk averters and increases it for risk lovers. Note that even the effect of increased returns to education μ_s interacts with risk attitude. An increase in returns will only increase optimum schooling length if $\alpha_s < 1/\sigma_s^2$. Strongly risk averse individuals may use the increased returns to shy away from further risky investments.

The schooling gradient of risk plays an important role in predicting outcomes, but is seldom analysed, in spite of the fact that at least crude information can be easily obtained from earnings variance by level of education, either as directly observed or after controlling for age or experience (cf. Hartog, Van Ophem and Bajdechi 2003).

III. Cross-section estimates for Spain

A. Basic specification

Both the survey of the literature and the model developed above indicate that the effect of post-schooling earnings variance on demand for schooling length is not unambiguous and will depend on the schooling gradient of risk and on risk attitudes. Hence, empirical work is needed to establish this sensitivity. We will explain the decision to continue education at the university level or not after completing secondary education.[7] Among the explanatory variables we include return, measured as the ratio of lifetime earnings with university or secondary education, and risk, measured as the ratio of residual earnings variances for the two educations. Both are measured in an individual's region of residence. Conceptually, the earnings residual will contain a stochastic component and individual heterogeneity. But as discussed above, we are not convinced that individuals at the time of deciding on their education have good knowledge of their individual heterogeneity component. The amount of human capital produced in school, their aptitude for the occupation they work in are typically only revealed in actual practice. Treating them just as risk at the time of decision making may thus very well be a realistic approach.

Our empirical strategy has two stages. We estimate earnings functions within regions, separately for workers just possessing secondary education and their counterparts possessing higher education.[8] From these we derive regional measures

[7] Figure A1 in the appendix summarizes the educational system in Spain during the 1970s, 1980s and early 1990s. We refer to these years, since individuals in our sample deciding whether to attend higher education make the choice during this period.

[8] At this stage we consider high-school and vocational education together for two reasons; firstly, wage differentials between them are negligible; secondly, although with smaller probability, individuals that have attended vocational education still have the possibility to attend higher education.

of returns to university education μ and the risk gradient γ (the ratio of residual earnings variance for university graduates' relative to secondary school graduates). We use these regional measures as explanatory variables in a probit for college attendance of youth. All information is taken from the same dataset, the Spanish Family Budget Survey 1990/91 (Encuesta de Presupuestos Familiares-EPF 1990/91), a nationally representative survey among 21155 households, collecting information on all 72123 individual household members. The survey respondents are pensioners, unemployed, workers and any individual living in the household aged 16 and above. In our sample, 7399 individuals out of the 72123 respondents are wage earners possessing secondary (4485) or higher education (2914). We use these observations to estimate earnings functions separately for university and secondary education in an individual's region of residence as a simple quadratic function of potential experience (age-education-6) and a dummy for gender (alternative specifications of the earnings function will be discussed below).[9] There are 18 regions (Comunidades Autónomas) in Spain. We have kept the specification of the earnings function deliberately sparse. Several potential variables that may have an impact are not known to the individual when deciding on university attendance. Other variables are allowed to have an impact only in the participation decision for reasons of identification (this holds in particular for the family background variables, which are known to have a small effect on earnings anyway).

More formally, to proxy the return (μ) and the risk gradient (γ) used as covariates in our schooling choice model, we first estimate Mincer wage equations as:

$$Y_{ijk} = \alpha_{jk} + \beta_{jk} X_{ijk} + \delta_{jk} X_{ijk}^2 + \gamma_{jk} G_{jk} + u_{ijk} \tag{11}$$

and

$$Y_{ijkg} = \alpha_{jkg} + \beta_{jkg} X_{ijkg} + \delta_{jkg} X_{ijkg}^2 + u_{ijkg}, \tag{12}$$

where the subscript j refers to each of the 18 regions, g refers to gender, and k is the

[9]We applied OLS, since variables to correct for selectivity and endogeneity bias are not available. However, in related work including a Heckman correction had little effect. See Diaz-Serrano (2001).

schooling level (*se:* secondary education; *he:* higher education) the individual i belongs to. Y are gross yearly wages, X are years of experience and G is a dummy for gender.[10]

We define the return as the ratio of lifetime earnings between individuals possessing higher education and secondary education calculated by gender and region:

$$return_{jg} = \frac{\sum_{t=0}^{42} \hat{y}_{t,he} / (1+r)^t}{\sum_{t=0}^{47} \hat{y}_{t,se} / (1+r)^t} , \tag{13}$$

where $\hat{y}$ are the estimated earnings from (11) or (12), $r=0.035$ is the discount rate, and the subscript t refers to years of experience.[11] We define risk as the ratio of the variance of the estimated residuals between individuals possessing higher education and those possessing secondary education:

$$risk_{jg} = \frac{\mathrm{var}(\hat{\varepsilon}_{i,he})}{\mathrm{var}(\hat{\varepsilon}_{i,se})} , \tag{14}$$

where $\hat{\varepsilon}$ is the exponential of the estimated residual from equation (11) or (12). The resulting estimates of returns and risk, as the counterparts to μ and γ used in equation (6), and the sample sizes for each are presented in Table 1. In Table 1, we refer to Model 1 when risk and return are calculated from equation (11) and to Model 2 when they are calculated from equation (12). The lifetime earnings mark-up for university education varies across regions between 1.19 and 1.74 for men and between 1.21 and 1.91 for women. Dividing by a length of education of 5 years would give a crude return per year of education between 3.8 and 18.2 percent; the latter is on the high side, but otherwise the returns are comparable to what has been reported in the international literature. Values for γ below 1 dominate, with a lower earnings risk for university than for secondary education. Thus in most Spanish regions university education reduces risk. As noted above, international evidence on the relationship between level of education and risk is conflicting:

[10] Detailed sample sizes for each estimate of equations (11) and (12) are available from the authors upon request.

[11] It is common practice to discount university earnings starting in year 6 and ending in year 47. The difference with our discounting is immaterial.

there is no universal positive or negative slope (Chen 2005, Hartog, van Ophem and Bajdechi 2003).

Table 1. Sample size, return and risk by region and gender

			Model 1				Model 2			
	Sample size		Return		Risk		Return		Risk	
Region	Men	Women	Men	Women	Men	Women	Men	Women	Men	Women
1. Andalucía	675	372	1.556	1.859	0.341	0.470	1.532	1.963	0.328	0.420
2. Aragón	253	165	1.336	1.361	1.196	0.855	1.273	1.510	1.111	0.962
3. Asturias	101	48	1.277	1.365	0.912	1.274	1.328	0.759	0.746	0.860
4. Baleares	95	71	1.263	1.214	1.161	0.706	1.243	1.427	1.148	0.758
5. Canarias	178	102	1.632	1.726	0.449	0.584	1.648	2.112	0.429	0.622
6. Cantabria	96	57	1.748	1.262	0.804	1.484	1.733	1.712	0.815	1.407
7. Castilla-La Mancha	638	415	1.328	1.705	0.874	0.667	1.337	1.632	0.863	0.597
8. Castilla-León	285	178	1.585	1.751	0.759	0.438	1.559	2.034	0.715	0.455
9. Com. Valenciana	474	277	1.573	1.576	0.975	0.294	1.576	1.570	0.920	0.302
10. Cataluña	317	204	1.370	1.592	0.614	1.068	1.294	1.924	0.598	1.084
11. Extremadura	119	74	1.668	1.452	1.817	0.619	1.706	1.465	1.573	0.702
12. Galicia	324	211	1.503	1.564	0.319	0.530	1.509	1.632	0.303	0.576
13. Madrid	250	145	1.288	1.349	0.092	0.591	1.294	1.223	0.087	1.061
14. Murcia	101	62	1.509	1.475	0.621	4.167	1.457	1.365	0.539	5.459
15. Navarra	122	67	1.194	1.577	1.839	0.592	1.259	1.524	2.519	0.503
16. País Vasco	447	259	1.561	1.690	0.771	0.702	1.563	1.696	0.792	0.694
17. Rioja	84	71	1.575	1.910	1.880	1.442	1.450	2.405	1.808	1.387
18. Ceuta y Melilla	46	16	1.320	1.860	0.598	0.345	1.406	0.963	0.335	0.270

Note: Model 1 refers to estimates coming from earnings functions according to equation (11); Model 2 refers to estimates coming from earnings functions according to equation (12).

One might be concerned about the fact that for some cells in table 1 the number of observations is too small to expect the estimates of return and risk to be representative. In order to test this we have estimated some confidence intervals for the estimates of risk in some cells. The estimate of risk for men in region 1 and model 1 is 0.34 with a confidence interval of [0.28, 0.39] and 675 observations. In the case of men living in region 18 for model 1 we get an estimate of risk of 0.59 with a confidence interval of [0.19, 1.32] and 46 observations. So far we get that for large groups as the first one, the estimated values are quite representative with small confidence intervals. In the case of the smallest groups as the second one with just 46 observations, the gap between the estimated value and the lower and upper value of the confidence interval is substantial. To test whether the small groups have a relevant incidence in the probit estimates, we have carried out additional estimates using just the cells with more than 50 observations. We observe that the effect of these groups of observations is quite modest, and that the differences with respect to the estimates that use the full sample are practically negligible.

We apply a probit model to estimate the probability to attend higher education once secondary education has been completed: the endogenous variable takes the value 1 if an individual possessing secondary education is attending higher education and zero otherwise. To estimate our choice equation we construct a sample of youth aged between 17 and 23, with secondary education completed. 17-18 years old is the usual age to complete secondary education and attend college, whereas 22-23 years old is the usual age of higher education completion. We only include individuals in the sample of youth if they are registered as member of the parental household (sons and daughters). It is quite common in Spain for youth in the given age bracket to live with their parents, no matter whether they work or go to school; we show some figures and discuss possible selectivity bias in the next section. Our final sample of youth consists of 2501 observations, of which 1521 are attending higher education and 980 do not, 1277 are males and 1224 are females.

Relating educational decisions to earnings variables at the level of the residential region only makes sense if information at this level is the prime input in the decision. This is probably a fairly acceptable approach, as individuals generally collect information in their near environment. There may be individuals with a clear perspective on the region where they might hope to work after graduation, e.g., a youth growing up in poor Extremadura anticipating earnings consequences in wealthy Madrid as the dream destination for a career. While such effects cannot be ruled out, we assume the regional environment to dominate as the main source for expected earnings consequences of schooling. The assumption is at least partially supported by the fact that in Spain very few students attend university education outside their own region. Moreover, it is strongly supported by information from a recent panel data set containing information on migration out of one's region of birth.[12] The data indicate that, on average, during the 1990's among individuals with higher education only some 3-5 percent left their region of birth between the ages of 23 to 25. This is the group that may have migrated soon after completing university. And they may have anticipated this, by considering pay-off to university education outside their own region. A better method to assess the pay-off to university education would then be a weighted average of the pay-off in the potential student's own region and in the other regions, with weights given by the probabilities of migration destinations after college. But with total weight of these other regions, in the relevant age bracket, restricted to 3 to 5 percent, one may hardly expect a substantial effect from such a refinement.

Our baseline probit estimates are given in Table 2. They differ in the specification of the underlying earnings function: Model 1 uses returns and risk estimated with regional earnings functions that include a dummy for gender (equation 11), whereas in Model 2 returns and risk are estimated by means of separate regional earnings functions by gender (equation 12), and thus includes gender-specific slopes. Generally, Model 2 would be preferable, but there is a cost in terms of small numbers of observations (see Table 1). We report two versions of each model: model B and D, which are the most complete versions of the probit model 1 and 2, respectively, and model A and C, which are the most parsimonious version of each model. We first focus on the most complete specifications of both models (B and D) and leave comments about models A and C for the next section. We observe that family characteristics have the conventional, and mostly highly significant effect on the probability to attend university after having completed secondary education. Family income, homeownership, parental education and occupation level of the household head has a positive effect, whereas family size reports a negative one. Urbanisation has a positive effect, while city size has a positive effect except for the initial dip

[12] We use the 1994-2000 waves for Spain of the European Community Household Panel (ECHP).

Table 2. Probit estimates for demand for higher education

	Model 1						Model 2					
	Model A			Model B			Model C			Model D		
	Coef.	m.e.	s.e.	Coef.	m.e.	s.e.	Coef.	m.e.	s.e.	Coef.	m.e.	s.e.
Constant	- 6.367		0.692***	- 4.006		0.843 ***	- 5.925		0.659 ***	- 3.644		0.819 ***
return	0.555	0.213	0.178***	0.672	0.253	0.194 ***	0.241	0.092	0.114 **	0.368	0.139	0.125 ***
risk	- 0.134	- 0.051	0.059***	- 0.136	- 0.051	0.062 **	- 0.075	- 0.028	0.045 *	- 0.085	- 0.032	0.048 *
log(*H-income*)	0.414	0.158	0.044***	0.217	0.082	0.057 ***	0.412	0.157	0.044 ***	0.216	0.081	0.056 ***
log(*H-size*)				- 0.525	- 0.198	0.105 ***				- 0.531	- 0.200	0.105 ***
home ownership				0.124	0.047	0.064 *				0.120	0.046	0.064 *
H-head education:												
primary				0.299	0.113	0.083 ***				0.297	0.112	0.083 ***
secondary				0.661	0.219	0.115 ***				0.663	0.219	0.115 ***
3-*year college*				0.989	0.293	0.148 ***				0.970	0.288	0.148 ***
5-*year college*				1.311	0.351	0.163 ***				1.311	0.351	0.163 ***
H-head occupation:												
manager farm				0.367	0.128	0.135 ***				0.362	0.127	0.135 ***
blue-collar farm				- 0.101	- 0.038	0.160				- 0.097	- 0.037	0.162
professionals				0.173	0.064	0.078 **				0.170	0.063	0.078 **
manager				0.464	0.162	0.117 ***				0.470	0.164	0.117 ***
white-collar				0.289	0.105	0.076 ***				0.290	0.105	0.076 ***
not classified				0.424	0.145	0.222 *				0.417	0.143	0.221 *

Table 2. (Continued) Probit estimates for demand for higher education

	Model 1						Model 2					
	Model A			Model B			Model C			Model D		
	Coef.	m.e.	s.e.	Coef.	m.e.	s.e.	Coef.	m.e.	s.e.	Coef.	m.e.	s.e.
City size:												
10.000-50.000				- 0.401	- 0.156	0.212 *				- 0.411	- 0.160	0.211 *
50.000-100.000				- 0.466	- 0.178	0.207 **				- 0.483	- 0.184	0.206 ***
100.000-500.000				- 0.437	- 0.170	0.213 **				- 0.428	- 0.167	0.213 **
>500.000				- 0.112	- 0.043	0.091				- 0.116	- 0.044	0.091
urbanization				0.486	0.185	0.186 ***				0.499	0.190	0.186 ***
job seeking				0.149	0.056	0.080 *				0.172	0.065	0.080 **
Log likelihood		-1602.5			- 1462.4			- 1606.32			- 1464.92	
Wald test		144.16			332.51			136.53			331.17	
Sample size		2501			2501			2501			2501	

Note: Probit estimates include dummies for region. Model 1 refers to estimates coming from earnings functions according to equation (11); Model 2 refers to estimates coming from earnings functions according to equation (12); s.e.: standard error; m.e.: marginal effect; * Significant at 10 percent level; ** Significant at 5 percent level; *** Significant at 1 percent level. H stands for “household” in *H-income*, *H-size* and H-head education; manager farm and blue-collar farm refer to occupation in farming, whereas professionals, managers, and white collar refer to occupation in industry and services.

(the effect of both variables should be interpreted together). The variable called unemployment is the region's average duration of unemployment so far for unemployed with a secondary education. It has a positive effect, which is understandable from lower opportunity cost.[13] Although they are not displayed in Table 2, we also consider regional dummies. They are included in order to assess whether the effect of our key variables (i.e., return and risk), which are computed by regions, is real or just picks up a pure regional effect. These regional fixed-effects are significant, and when they are included significance levels of the estimated coefficients for return and risk even increase, without effects on the magnitude of the coefficients. We conclude that differences between model 1 and 2 are not substantial.

The earnings ratio (return) has the expected positive effect, and significantly so. The earnings variance ratio (risk) has a negative effect, significant at 5 percent in model 1 and at 10 percent in model 2. Using the framework of equations (6) to (10), this indicates that risk aversion dominates the education decision for youth with completed secondary education, as there is a negative response to the schooling gradient of risk, i.e., the variance ratio between university and secondary education.[14] The ratio of the coefficients on return and risk measures the trade-off between risk and returns, or the marginal returns required to maintain constant probability of going to university when risk increases, where both returns and risk are measured in relative terms. Table 2 indicates that this trade-off is about -0.2: if the risk ratio increases by 10 percentage points (e.g., from 1.2 to 1.3), compensation requires an increase in the returns ratio by 2 percentage points.

At this point it is worth repeating that we use ex post variance in earnings as an indication of ex ante risk. In a market model, risk compensation will be imposed by supply reactions based on the risk perceptions of potential students. Ex post variance at the regional level will reflect individual heterogeneity in terms of ability, drive, job choices, etc., and cross-regional heterogeneity in industry composition, firm composition, etc., as well as risk because of the innate stochastic nature of technological and market relations. The latter arises as a given action or effort of

[13] The results are essentially the same if we use the ratio of unemployment duration by education.

[14] If we include regional fixed effects in the probits, the coefficients for returns and risk are barely affected, while their t-ratio's increase.

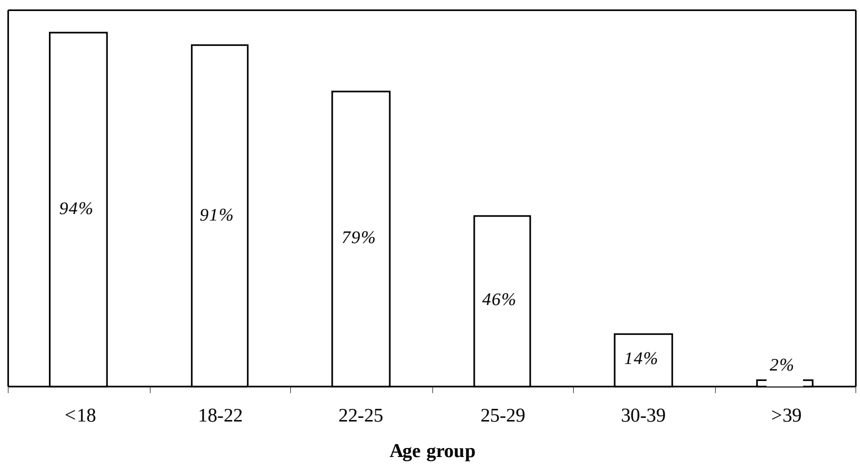
an individual does not generally lead to a given result, neither at the individual nor at the firm level. We assume that differences in ex-post variance reasonably approximate differences in individuals' perceived ex-ante risk and we have given some arguments for this assumption in the Introduction. But we see empirical research on individuals' actual perceptions as an important next step in this line of research.

B. Assessing robustness

We have tried to assess the robustness of our results in several ways. We have estimated two different specifications of the earnings functions. As can be seen in Table 1, there are some outliers in the explanatory variables. The risk ratio is exceptionally low for men in region 13 and exceptionally high for women in region 14. Region 13 is wealthy Madrid, region 14 is poor Murcia. We have no explanation for these outliers, but they do not drive the results. If we exclude them from our data set and re-estimate, the basic results retain, with returns and risk significant at 10 percent or better. As we mentioned in the previous section, in order to test whether the estimated coefficients of return and risk are robust to changes in the specification, we use more parsimonious versions of the probit model (model A and C in table 2). These models use as unique covariates return, risk, family income and a set of regional dummies. We focus on the estimates of our variables of interest, i.e., return and risk. We observe that the gap between the estimated parameters of the more parsimonious (A and C) and the most complete specification (B and D) is negligible, 0.55 vs. 0.57 and -0.13 vs. -0.12 in Model 1, and 0.24 vs. 0.26 and -0.07 vs. -0.07 in Model 2. These results indicate that the estimated effect of return and risk on the probability of attending higher education is very robust.

A particular concern may be that our sample is based on a household survey and that we catch only youth living with their parents. One may fear a selectivity bias here, as one might think working youth to be more inclined to leave the parental household than youth still in school. However, this is generally not so in Spain. It is quite common for youth to live in the parental household until at least their mid-twenties. In Figure 1 we show the percentage of sons/daughters living in the parental household by age groups. The age bracket 18-22 is the usual age for youth to enrol and complete college education. For this age group, the percentage of individuals living in the parental household is about 91 percent. For the age bracket 22-25, when higher education is supposed to be completed, we still observe a high percentage of youth living in the parental household, about 79 percent. In Figure 2 we show the occupational status of the youth aged 18-29 living at the parental household. About 49 percent of the youth aged 22-25 living in the parental household are currently employed with earnings, whereas among those aged 25-29 this percentage rises to 62 percent. The proportion of students within these age groups are 22 and 9 percent, respectively. Hence, it is clear that in Spain, and generally in the Southern European countries, having their own earnings is not critical for young workers when deciding to abandon the parental household. Marriage is the most usual reason. These figures show that the usual selectivity bias problem inherent to the US or UK evidence is not a prime concern in Spain.

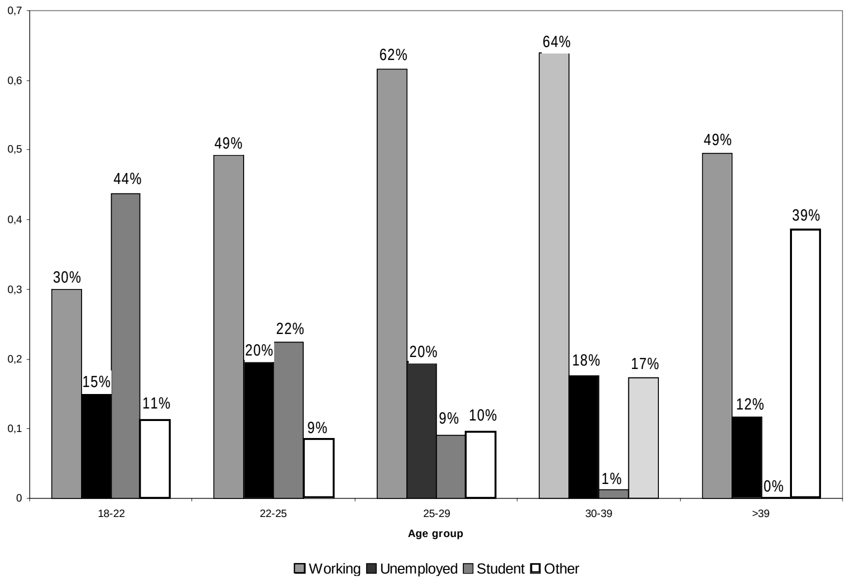
Figure 1. Percentage of sons/daughters living at the parental households by age groups



Source: Spanish Household Budget Survey 1990/91 (EPF 90/91)

As we needed information on parental background, we have restricted our sample of youth to “sons and daughters”, 93% of the individuals aged 17-23 in our sample. This means that we have excluded 54 household heads, 50 spouses, 77 other relatives and 33 non-relatives of the household head. If selectivity is a problem it should arise from these exclusions, as the sample is representative of all households. Thus, we re-estimated our models without restriction to sons and daughters, adding a dummy for household head or spouse and interaction for the

Figure 2. Distribution of the occupational status of the sons/daughter living at the parental household by age groups



Source: Spanish Household Budget Survey 1990/91 (EPF 90/91)

dummy and household income (for the case where income is own earned income, rather than the source for parental transfers). Extending the sample in this way, and thus including households of youth not living with their parents turns out to be immaterial.

C. Measurement errors

Finally, we consider the problem that really bothered us. Our key variables, returns and especially risk, are taken from the residuals in earnings functions and thus may be expected to contain measurement error or they may be biased by unobserved heterogeneity. This may bias our estimated coefficients. The analysis below suggests, however, that this effect is probably modest. In addition, we may note that we use ratio's of returns and variances, so it's the bias in returns and variances of university relative to secondary education that matters. If the bias is identical at both levels of education, there is no effect on our results.[15] Consider the linear relationship $y = X\beta_0 + \varepsilon$, where y can be an observed or latent variable, X contains the exogenous variables and ε a random error term. The problem arises when instead of X we observe Z, being $Z = X + u$, with u the associated measurement error. Consequently, when we estimate $y = Z\beta_0 + \varepsilon$, we have that $y = X\beta_0 - u\beta_0 + \varepsilon$. Then, OLS for the linear regression model, and ML estimation in the case of the probit, will provide a biased estimation of β_0 (the absolute value of the parameters will tend to be underestimated). The problem is similar to the case of endogenous regressors, and so instrumental variables (IV) estimation is one of the most common solutions to deal with measurement errors, see, e.g., Amemiya (1985) or Iwata (2000). Nevertheless, given the usual problem of the scarcity of appropriate instruments other ways to correct for errors-in-variables have been developed. For instance, one of the most common consists in the manipulation of the likelihood function, see, e.g., Li and Hsiao (2001). Others are based on the method of moments estimator (see Hong and Tamer 2003), or in minimum distance estimators, as Li (2000) and Hsiao (1989). We will use two different ways to assess the possible consequences of measurement errors in our probit estimates. They generate the same results and we conclude that the impact is fairly modest.

Define σ_ε^2, $\Sigma_u = \text{var}(u)$, $\Sigma_X = \text{var}(X)$, and $\Sigma_Z = \text{var}(Z)$. Hence, according to the equations written above we have that $\Sigma_X = \Sigma_Z - \Sigma_u$. According to this, the variance of the true exogenous variables X crucially depends on the variance of the measurement error u, which is unknown. This lack of knowledge of Σ_u implies some identification problems that lead to an inconsistent estimation of β_0 when the conventional ML estimation is used. If the measurement error problem is ignored, the inconsistent estimation of β_0 will converge to the following expression:

$$\beta_1 = \frac{\beta_0 \sigma_x^2}{\sqrt{\sigma_x^2 + \sigma_u^2}\sqrt{\sigma_x^2 + \sigma_u^2 + \beta_0 \sigma_x^2 \sigma_u^2}}\ , \tag{15}$$

[15] In Chen's analysis for the US, the bias was identical for "Less than High School" and "4 years College and more" and for "High School" and "Some College". Between these groups, it was different (Chen, 2005, Table 4, "uncertainty" as a fraction of variance, permanent component). Cunha et al (2005) also allow the share of forecastable variability to vary by education level.

where σ_x^2 and σ_u^2 are the variance of the true regressor X and the measurement error u, respectively. In equation (15), β_0 is the true parameter and β_1 its inconsistent estimator. In absence of measurement error, that is u=0 and $\sigma_u^2=0$, $\beta_0=\beta_1$. Equation (15) suggests that the greater the measurement error u, the greater σ_u^2. Therefore, the absolute value of β_0 will tend to be underestimated. Now, to assess the bias it is necessary to make some assumptions. In the presence of measurement errors we observe $Z=X+u$, and hence the variance of Z takes the following form $\Sigma_Z = \Sigma_X + \Sigma_u$. We know that due to measurement errors, a share of the variance of Z (known) is in Σ_X and the remaining variance is in Σ_u. In order to assess the bias, we will make the following assumption:

$$\begin{aligned} \Sigma_Z &= \Sigma_X + \Sigma_u = \alpha\Sigma_Z + (1-\alpha)\Sigma_Z \\ \Sigma_X &= \alpha\Sigma_Z \\ \Sigma_u &= (1-\alpha)\Sigma_Z \end{aligned} \tag{16}$$

Without measurement errors (α= 1), the variance of the true regressors X coincides with the variance of the observed Z.

To evaluate the potential bias we just have to develop expression (15) that yields:

$$\beta_0 = \frac{\beta_1(\sigma_x^2 + \sigma_u^2)\left(\beta_1\sigma_u^2 + \sqrt{\beta_1^2\sigma_u^4 + 4}\right)}{2\sigma_x^2}. \tag{17}$$

As β_1 we take our probit estimations for return and risk in Table 1. Under the presence of measurement errors, according to equation (17) and assumption (16), the theoretical true value of β_0 depends on α. Now, suppose that we interpret the results of Baker and Solon (2003) cited above, that permanent shocks count for two thirds of inequality and transitory shocks for one third, as indicative of the share of measurement errors, and set the share of true variance α =0.7. Then, compared to the interpretation of no measurement errors (α =1.0), the effect is modest, as Table 3 shows.

According to expression (15), a consistent estimator of β_0 can be achieved by applying the following transformation over Z (see Iwata 1992):

$$\hat{X} = Z\hat{\Sigma}_Z^{-1}\hat{\Sigma}_X. \tag{18}$$

Table 3. Effect of measurement error using equation (17)

	Model 1		Model 2	
α	β_0(*return*)	β_0(*risk*)	β_0(*return*)	β_0(*risk*)
1.0	0.6721	-0.1365	0.3682	-0.0850
0.9	0.7476	-0.1515	0.4096	-0.0943
0.8	0.8418	-0.1701	0.4614	-0.1059
0.7	0.9631	-0.1941	0.5279	-0.1208
0.6	1.1247	-0.2261	0.6166	-0.1407
0.5	1.3510	-0.2709	0.7408	-0.1686

Note: Simulations are based on the estimated coefficients of model B and D in Table 1. Model 1 refers to estimates coming from earnings functions according to equation (11); Model 2 refers to estimates coming from earnings functions according to equation (12).

Conventional probit estimation using (18) provides consistent estimators. To estimate $\hat{\Sigma}_X$ we use again assumption (16). The results are reported in Table 4.

Table 4. Effects of measurement error using equation (18)

		Model 1		Model 2	
α		Coef.	s.e.	Coef.	s.e.
1	*return*	0.6721	0.194 ***	0.3682	0.125 ***
	risk	-0.1365	0.062 **	-0.0850	0.048 *
0.9	*return*	0.7467	0.216 ***	0.4092	0.139 ***
	risk	-0.1516	0.069 **	-0.0945	0.054 *
0.8	*return*	0.8401	0.243 ***	0.4603	0.157 ***
	risk	-0.1706	0.078 **	-0.1062	0.060 *
0.7	*return*	0.9600	0.277 ***	0.5261	0.179 ***
	risk	-0.1949	0.089 **	-0.1214	0.069 *
0.6	*return*	1.1201	0.324 ***	0.6138	0.209 ***
	risk	-0.2275	0.103 **	-0.1416	0.080 *
0.5	*return*	1.3441	0.388 ***	0.7365	0.251 ***
	risk	-0.2729	0.124 **	-0.1699	0.097 *

Note: Simulations are based on the estimated coefficients of model B and D in Table 3. Model 1 refers to estimates coming from earnings functions according to equation (11); Model 2 refers to estimates coming from earnings functions according to equation (12); s.e.: standard error; * Significant at 10 percent level; ** Significant at 5 percent level; *** Significant at 1 percent level.

From Table 4 we also observe that not only the greater the error of measurement, the greater the true value of the parameter, but also the greater the variance. Both estimated parameters and their variance rise at the same proportion, thus significance levels are unaffected. Of course this is different if α differs between education levels (see footnote 12).

D. Allowing for heterogeneous risk attitudes

It is quite unlikely that all individuals will have identical risk attitudes. In particular, the evidence from direct measurement such as based on reservation prices for lottery tickets, shows marked variability between individuals (see Hartog, Ferrer-i-Carbonell and Jonker 2002 for evidence and references). Interestingly, the Spanish household survey, as an expenditure survey, has observations on expenditures on lottery tickets. Presumably, such expenditures reflect risk attitudes in the household. We created dummy variables to pick out households who spend more than x percent of the family budget annually on lottery tickets, with x running from 1 to 4. In our estimates we include both the dummy variable picking up the gambling propensities of the household, $lottery_i$, and the interaction term with the variance ratio, i.e., $risk_{jg} \cdot lottery_i$.

The different shares of income devoted to gambling are reported in Table 5. As Table 5 shows, the sample share so selected decreases from 32.4 to 9.6 percent from those households spending from 1 to 4 percent of the household income in lottery games, respectively. Estimation results for the choice equation including risk attitudes are presented in Table 6.[16] They are precisely in the expected direction, with a strong dampening of the negative effect of the risk gradient, and in fact, a

Table 5. Number of individuals with a given % of income spent in lotteries

% of the household income spent in gambling	1 %	2 %	3 %	4 %
# of individuals (sample size=2501)	810	517	337	239
% of the sample (sample size=2501)	32.4	20.7	13.5	9.6

[16] For these estimates we use the most complete specification as in model B and D.

sign reversal for those who spend relatively more on lotteries. Compared to the results in Table 2, the negative response to relative risk is quite stable as we use dummies for higher lottery shares. But for strong lottery adepts, the countering positive effect becomes so strong that it even surpasses the primary effect and generates a positive balance: those who spend much on lotteries even react positively to increases in the risk ratio. For households without participation in lotteries, the required compensation for increased risk, as discussed at the end of Section III.A, is about 0.35 (0.323 for Model 1, 0.376 for Model 2, see Table 6). For households spending 4% or more on lotteries, this compensation is about - 0.35 (bottom panel of Table 6); such households behave like risk lovers.

The estimates of the risk-return trade-off (e.g., Model 1, Table 6) for different risk attitudes are -0.02, 0.07, 0.203 and 0.204 for a 1, 2, 3 and 4 percent of expenditure in lottery games, respectively. Alternatively, if we assume that the expenditure in lottery is null, the same models (see Table 6) report a risk-return trade-off of -0.322,

Table 6. Probit estimates for demand for higher education with alternative gambling dummies

	Model 1			Model 2		
	Coef.	m.e.	s.e.	Coef.	m.e.	s.e.
return	0.6919	0.2608	0.201 ***	0.3724	0.1404	0.129 ***
risk	- 0.2234	- 0.0842	0.082 ***	- 0.1402	- 0.0528	0.063 ***
*risk*lottery* (1%)	0.2089	0.0787	0.111 *	0.1267	0.0477	0.087
return	0.6940	0.2616	0.201 ***	0.3839	0.1448	0.128 ***
risk	- 0.2035	- 0.0767	0.072 ***	- 0.1304	- 0.0492	0.055 ***
*risk*lottery* (2%)	0.2532	0.0955	0.129 **	0.1584	0.0597	0.100
return	0.6783	0.2557	0.201 ***	0.3760	0.1418	0.129 ***
risk	- 0.1907	- 0.0719	0.072 ***	- 0.1261	- 0.0475	0.055 ***
*risk*lottery* (3%)	0.3290	0.1240	0.138 ***	0.2416	0.0911	0.107 ***
return	0.6738	0.2540	0.201 ***	0.3745	0.1412	0.129 ***
risk	- 0.1830	- 0.0690	0.070 ***	- 0.1212	- 0.0457	0.054 ***
*risk*lottery* (4%)	0.3200	0.1206	0.146 **	0.2424	0.0914	0.113 **

Notes: Probit estimates include dummies for region and for lottery shares (*lottery*). Simulations are based on the estimated coefficients of model B and D in Table 2. Model 1 refers to estimates coming from earnings functions according to equation (11); Model 2 refers to estimates coming from earnings functions according to equation (12); s.e.: standard error; m.e.: marginal effect; * Significant at 10 percent level; ** Significant at 5 percent level; *** Significant at 1 percent level.

-0.293, -0.281 and -0.271, respectively.[17] This means that for the former group, who are supposed to be "risk-averse", if the risk ratio increases by 10 percentage points (eg from 1 to 1.1), compensation requires an increase in the returns ratio around say 3 percentage points in order to maintain constant the probability of going to university. On the contrary, for "non risk-averse", "risk-neutral" or "risk lovers" results change drastically. For households expending 1 percent of annual income in lottery games the compensation required if the risk ratio increases by 10 percent is just about 0.2 percent. Indeed, for households expending 2, 3 and 4 percent the compensation becomes negative. These results are a strong support for one of our key predictions, i.e., a pivotal role for risk attitudes.

IV. Concluding remarks

The literature on the effect of uncertain returns to education on the decision to invest generates no unequivocal results. We have contributed to that literature by developing a simple basic investment model that lays out the pivotal role of risk attitudes and the schooling gradient of earnings risk in determining the sign of the relationship. Our estimates for Spain document the schooling risk gradient and support our conclusion on the importance of risk attitudes. We measure the returns to university education as the ratio between lifetime earnings from university education relative to lifetime earnings from secondary education only, and we measure risk as the ratio of residual variance for university graduates relative to those who completed secondary education. Returns have a positive effect on the inclination to attend university, risk has a negative effect: the higher the risk, the lower the investment in education. The conclusion is robust to eliminating outliers in estimated risk, restricting the subset of youth to tighter conditions on belonging to the family, to measurement errors and to endogeneity. We also find conventional effects of family background: higher income, wealth and education in the parental household stimulate university education. Higher unemployment in the region also stimulates university attendance, as it reduces the opportunity cost. We find a marked effect of risk attitudes, fully in line with our analytical model: declining risk aversion reduces the impact of risk on university attendance. We conclude that the basic model we have presented here is a very useful vehicle for more empirical work along these lines.

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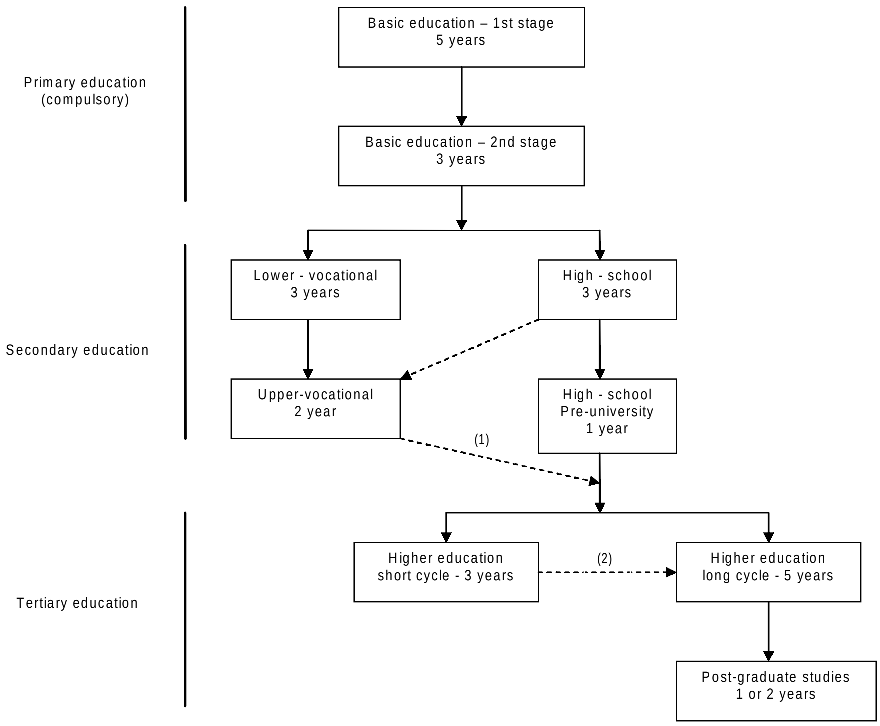
[17] The risk-return trade-off are estimated using the estimated coefficients of the variables *risk*, *risk*lottery* and *return*. The first estimates of the risk-return trade-off come from the ratio *(risk-risk*lottery)/return*, while the second ones come from the ratio *risk/return*.

The model we use, while generating essential insights, can certainly be improved by building on less restrictive assumptions. The most urgent candidate for change would be the assumption that individuals must make a single binding decision on their length of education. In that sense, dynamic optimisation models, where individuals adjust their decisions along the way, are more attractive. Yet, while no doubt providing interesting and relevant refinements, it is doubtful whether such modelling will substantially modify the conclusion on the key role of risk attitudes and the schooling gradient of earnings risk. Further empirical work seems more urgent, in particular seeking replication of the results reported here, and extending the set of observations on earnings risk. We also attach high priority to research into the risks that individuals perceive when deciding on schooling, and the impact of such perceptions for the actual decisions.

Appendix

Figure A1. Educational system in Spain during the 1970s, 1980s and early 1990s



Note: Basic education begins at the age of 6; (1) Up to 30 percent of the places for new students in higher education are offered to individuals coming from upper-vocational and training schools. Moreover, those with upper vocational and training education can only chose among a limited set of fields; (2) Individuals with 3 complete years of college can obtain a Bachelor's degree by spending 2 more years in college.

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