EARNINGS RISK AND DEMAND FOR HIGHER EDUCATION:

A CROSS-SECTION TEST FOR SPAIN

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Abstract

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.

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

The literature starts with Levhari and Weiss (1974), with Eaton and Rosen (1980), Kodde (1985) and Jacobs (2002) building on their model. Levhari and Weiss 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.[1]

Williams (1979) is the first to apply a stochastic dynamic programming model to education decisions, and to link 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

[1] Kodde (1985) identifies an additional, implicit, requirement for this result.

strong and the covariance between depreciation and production of human capital is highly negative. Belzil and Hansen (2002) estimate a stochastic dynamic programming model on data from the NLSY 1979-1990, assuming a model with constant relative risk aversion (estimated at 0.928). 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 elasticity, at 0.07, is quite small though.

Hogan and Walker (2001) 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 low wage students stay in school anyway. As a results, individuals react by staying in school longer as risk increases.

The models differ somewhat in the concept of risk, but essentially they all consider the effect of changes in the variance of the post-school wage. The predictions are different though: increased risk may increase or decrease the length of schooling. The differences can be explained from differences in model structure, each highlighting different channels through which risk appears. Obviously, risk has many faces, and individuals can react in many ways. In this paper, we develop 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 in a simple elegant formula. 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.

2. Length of education with stochastic earnings

2.1 *A simple formula*

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 shift parameter and θ_{st} is a stochastic variable.[2] For a start, simplify to θ_{st}=θ_s and

$$\begin{aligned} &E\left(\theta_s\right) = 1 \\ &E\left\{\theta_s - E\left(\theta_s\right)\right\}^2 = \sigma_s^2 \end{aligned} \tag{2}$$

θ_s is a stochastic shock around Y_s, with a single lifetime realisation, but with variance dependent on schooling length s. This simple specification is similar in spirit to Levhari and Weiss's two period model, with a wage unknown when deciding on schooling, but

[2] 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.

with a single lifetime realisation (one wage rate for the entire post-school period). Chen (2001) argues that transitory shocks are less important because they can be averaged out over one's lifetime, while permanent shocks persist; she finds, for the US, that permanent shocks account for 50 to 60% of unexplained earnings variance of high school and college educated workers. 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. As individuals cannot insure this risk, write the individual objective as maximum expected lifetime utility, discounted at rate ρ

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

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

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

Then, rewrite the objective function as

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

Setting the derivative to s equal to zero, ignoring a term with $U'''\left(Y_s\right)$ 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. To understand this expression, note

- if $\sigma_s^2 = \frac{\partial \sigma_s}{\partial s} = 0$ and $\varepsilon_s = 1$, we have the standard condition of the core Becker-Mincer model, with investment up to the point where discount rate and marginal rate of return are equal. These conditions specify a riskless world and lifetime earnings maximization.
- if $\sigma_s^2 = \frac{\partial \sigma_s}{\partial s} = 0$ and $\varepsilon_s \neq 1$, we have the modification of utility maximization rather than earnings maximization.
- if individuals are risk neutral $(\alpha_s = 0)$ we have the same result as when there is no risk $(\sigma_s^2 = 0, \textit{all } s)$.[3]

The second-order condition for an optimum requires the left-hand side of equation (6) to be a downward sloping function of s. By consequence, anything that shifts the curve upwards has a positive effect on optimum schooling (which occurs at intersection with the

[3] Note that $\alpha_s = 0$ implies U"= 0, hence U' is constant, or $\varepsilon_s = 1$.

zero-axis and is shifted to the right), and anything that shifts the curve down reduces optimum schooling.

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 $\left(\mu_s + \gamma_s > \frac{1}{2}\rho\right)$, an increase in risk, at 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 $\left(\gamma_s < \frac{1}{2}\rho - \mu_s\right)$ 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 non-standardised data are widely available. It calls for a search for empirical regularities (cf Hartog, Van Ophem and Raita, 2003).

2.2 G*eneralisation*

We will now develop a very general result, subject to only one substantial restriction. We will assume that stochastic shocks to earnings at different ages are uncorrelated. Correlated shocks will probably not affect the key result that with risk aversion, investment will be lower when risk increases, while the reverse holds for risk lovers.

Assume a general earnings profile $\theta_{st} Y_{st}$ where Y_{st} is non-stochastic and θ_{st} is the stochastic shock at age t, for given education s, with

$$E(\theta_{st}) = 1\ ,\ all\ \ s,\ t \tag{11}$$

$$E\{\theta_{st} - E(\theta_{st})\}^2 = \sigma_{st}^2 \tag{12}$$

$$E\{\theta_{st} - E(\theta_{st})\}\{\theta_{sv} - E(\theta_{sv})\} = 0\ ,\ t \neq v \tag{13}$$

As before, the individual is assumed to maximize expected lifetime utility

$$\mathrm{W} = \mathrm{E}\int_s^\infty E\{\theta_{st} Y_{st}\} e^{-\rho t} dt = \int_s^\infty e^{-\rho t} E\{U(\theta_{st} Y_{st})\} dt \tag{14}$$

because of independent errors. Applying, as before, a second-order Taylor series expansion, we get

$$\mathrm{W} = \int_{\mathrm{s}}^\infty e^{-\rho t}\left[U(Y_{st}) + \frac{1}{2}U''(Y_{st}) Y_{st}^2 \sigma_{st}^2\right] dt \tag{15}$$

Setting the first derivative of W to s equal to zero, in a similar development as the derivation of (6), including ignoring a term with U''' yields the condition

$$\begin{aligned} \frac{\partial \mathrm{W}_s}{\partial s} &= -\left[\varepsilon_{ss}^{-1} - \frac{1}{2}\alpha_{ss}\sigma_{ss}^2\right] U'_{ss} Y_{ss} e^{-\rho s} + \\ &+ \int_s^\infty \left[\mu_{st} - \alpha_{st}\sigma_{st}^2(\mu_{st} + \gamma_{st})\right] U'_{st} Y_{st} e^{-\rho t} dt = 0 \end{aligned} \tag{16}$$

$$\mu_{st} = \frac{\partial Y_{st}}{\partial s}\frac{1}{Y_{st}} \geq 1 \tag{17}$$

$$\gamma_{st} = \frac{\partial \sigma_{st}}{\partial s}\frac{1}{\sigma_{st}} \tag{18}$$

$$\alpha_{st} = \frac{U''(Y_{st})}{-U'(Y_{st})} Y_{st} \tag{19}$$

$$\varepsilon_{st} = \frac{\partial U(Y_{st})}{\partial Y_{st}} \frac{Y_{st}}{U(Y_{st})} > 0 \tag{20}$$

Now, we have essentially the same result as before.[4] As the second order condition requires $\partial^2 W_s / \partial s^2 < 0$, we know that $\partial W_s / \partial s$ is declining in s. Then, as before, a positive effect of some variable on the derivative increases optimal education (the intersection of the curve with the zero axis), a negative effect decreases optimal education. The conclusions are slightly different from those of the simpler case, but important results remain. And now of course conclusions pertain to age-specific variables and parameters, rather than single lifetime values. A sign reversal of α_{st}, from risk aversion to risk loving, switches the sign of the effect of changes in variance σ_{st}^2 and in risk gradient γ_{st}. A change in σ_{ss}^2, variance at the start of working life, has a different effect than a change in a later year: it adds a positive term for risk averters, a negative term for risk lovers. An increase in later variance (t > s), reduces optimum schooling lengths for risk averters, unless the slope gradient annihilates the effect of the rate of return $(\mu_{st} + \gamma_{st} < 0)$. An increase in the schooling gradient of risk will have a negative effect on schooling length for risk averters. Note that indeed risk averters may be induced to lengthen their schooling if the schooling gradient of risk is sufficiently negative. Our key general conclusion remains: the sensitivity to risk depends essentially on risk attitudes and there is an important role for the schooling gradient of risk. The first conclusion is no surprise, although existing models do not all allow for a full range

[4] Note, as before, that earnings maximisation implies unitary elasticity, $\alpha_{st} = 0$, $U'_{st} = 1$. With income independent of age, the standard Mincer condition returns.

of risk attitudes. The second conclusion indicates that empirical work is needed to establish the nature and determinants of the schooling gradient of earnings risk.

Needless to say our model is simpler and more restrictive than the dynamic programming models that are being developed. In particular, our assumption that individuals commit once and for all to an optimum schooling length ignores that individuals may adjust plans as they advance through education, and indeed, with growing information will see their risk from ignorance reduced. But our model has the virtue of highlighting the role of key parameters, and thus provide a useful frame for empirical analyses. Generalising the model to a correlated variance structure over time has no priority, as we do not anticipate surprises from it.

3. Cross-section estimates for Spain

3.1 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. Among the explanatory variables we include return, the ratio of lifetime earnings with university or secondary education, and risk, the ratio of residual earnings variances between the two educations. Both are measured at the level of an individual's region of residence.

In the Spanish system of education in the later 1980's and early 1990's[5], compulsory primary education was usually completed at ages 13-14. Children who complete it without a diploma can only continue in lower vocational schools. Those who complete with a diploma almost all choose high school. After lower secondary (lower vocational or high school), individuals can leave the educational system if they want and start working. Most usual is to continue, from lower to upper vocational and from high school to pre-university. Almost 100% of those who complete pre-university attend higher education. Among students completing upper vocational, most of them start working and a very small fraction attend higher education; they have a smaller range of degrees to choose from. The normal age to complete secondary education and attend higher education was 17-18 years old. Students who have decided to attend higher education can choose a short university degree (3 years college) or a long university degree (5 years college-this is a bachelor). Individuals who have completed the short-cycle may start working or they can complete the long cycle in 2 or 3 years more (depending on the short degree completed and the long degree selected). The age to complete the short degree was 20-21 and the long degree 22-23.

Our empirical strategy has two stages. We estimate earnings functions within regions, separately for secondary educated and university educated workers. From these we derive regional measures 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 model for college attendance of youth. All information is taken from the same dataset, the

[5] We refer to these years, since individuals in our sample deciding whether to attend higher education make the choice during this period.

Spanish Family Budget Survey 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, 7400 individuals out of the 72123 respondents are wage earners possessing secondary (4486) 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 minus education) and a dummy for gender (alternative specifications of the earnings function will be discussed below; see Appendix A for definitions and specifications)[6]. There are 18 Autonomous Regions 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). We approximate the regional rate of return to university education by dividing discounted lifetime earnings with university education by discounted lifetime earnings with secondary education, with age-specific annual earnings derived from the estimated earnings functions. We put the discount rate at 3.5%. Regional risk is measured as the ratio of the residual variance in the region from the earnings function for the university educated to the residual variance for the secondary educated[7].

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[6] 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).

[7] More precisely: it is the variance of the exponential of the estimated residuals in the log earnings function.

The resulting estimates of returns and risk, as the counterparts to μ and γ used in equation (6), are presented in Table 1. The lifetime earnings mark-up for university education varies 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. International evidence on the relationship between level of education and risk is conflicting: there is no universal positive or negative slope (Hartog, van Ophem and Bajdechi, 2003).

Insert table 1 here

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 one if the individual possessing secondary education is attending higher education and zero otherwise. To estimate our choice equation we construct a sample of young aged between 17-23, with secondary education completed. As we mention at the beginning of this section, 17-18 years old is the usual age to complete secondary education and attending college, whereas 22-23 years old is the usual age of higher education completion. We only include individuals in the sample of young 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 discuss possible selectivity bias in the next section. Our final sample of young contains 2501 observations, from whose 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 a small fraction of students attend university outside their own region. Moreover, it is strongly supported by information from a recent panel data set [8] with information on migration out of one's region of birth. The data indicate that in the 1990's among individuals with higher education some 5% have left their region of birth between the ages of 20 to 30. This is the group that may have left to go to university or 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

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

bracket, restricted to 5%, one may hardly expect a substantial effect from such a refinement.

We should also stress that we use contemporaneous information on returns and risk to explain the university participation decision. We firmly believe that this is a proper approach, reflecting the information individuals have available at the time of the decision. An alternative might be to use panel data for individuals' earnings to extract information on returns and risk. The information might then be used to explain the schooling decision that individuals have taken in the past. This is a very strong assumption, as it implies that the information that we as researchers deduce from the individual's post-school earnings profile was available to the individual when deciding on schooling. We think that the assumption of using contemporaneous information in the individuals' environment is a much more reasonable approach. But of course, ultimately this can only be decided by proper empirical testing (for which at the moment we do not have the data).

Our baseline probits are given in Table 2. They differ in the specification of the underlying earnings function: Model 1 has a dummy for gender, Model 2 has separate estimates by gender, 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 appendix A). Family characteristics have a conventional, and mostly highly significant effect on the probability to attend university after having completed secondary education. Family income, home ownership, parental education and occupation level have a positive effect, family size a negative effect. Urbanisation has a positive effect, while city size has a positive effect except for the initial dip (the effect of both variables should be interpreted together). The variable called "job seeking" 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.[9] Although they are not displayed in Table 2, we also consider regional dummies. They are included in order to assess whether the effect of the variables computed by regions (e.g. return and risk) 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 significant effects on the magnitude of the coefficients. We conclude that differences between model 1 and 2 are not substantial.

Insert table 2 here

The key variables are the earnings ratio and the earnings variance (see appendix A for a detailed description of the variables). The earnings ratio has the expected positive effect, and significantly so. The earnings variance ratio has a negative effect, significant at 5% in model 1 and 10% in model 2. Using the framework of equation (6) and (7), 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 risk ratio between university and secondary education.[10].

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

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

3.2. 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% or better.

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[11]. As we needed information on parental background, we have restricted our youth sample 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 dummy and household income (for the case where income is own earned income, rather than the source for parental transfers). Extending the sample in

[11] Some official Spanish statistics carried out by the National Statistics Bureau (INE) estimate this age at 29 years old at the end of the 1990's.

this way, and thus including households of youth not living with their parents turns out to be immaterial.

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. This may bias our estimated coefficients. In appendix B we measure to which extent our results may be affected by this problem. We conclude that this effect is probably modest.

3.3. 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 market 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 and other forms of gambling. Presumably, such expenditures reflect risk attitudes in the household. We created dummies to pick out households who spend more than x% of the annual family budget on lottery tickets, with x running from 1 to 5. As Appendix A (table 5) shows, the sample share so selected decreases from 32.4 to 7.2 %. We interacted the dummy with the variance ratio. Results are presented in Table 3. They are precisely in the expected direction, with a strong dampening of the negative effect of the risk gradient, and in fact, a sign reversal for those who spend relatively much 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 addicted, 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. This is strong support for one of our key predictions, i.e. a pivotal role for risk attitudes.

Insert table 3 here

4. 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 think that the basic model we have presented here is a very useful vehicle for more empirical work along these lines.

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.

Appendix A (definition of the variables)

To estimate the Return and Risk used as covariates in our schooling choice model we first estimate the following Mincer wage equations

$$Y_{ijk} = \alpha_{jk} + \beta_{jk} X_{ijk} + \delta_{jk} X_{ijk}^2 + \gamma_{jk} G_{jk} + u_{ijk} \tag{21}$$

and

$$Y_{ijkg} = \alpha_{jkg} + \beta_{jkg} X_{ijkg} + \delta_{jkg} X_{ijkg}^2 + u_{ijkg} \tag{22}$$

where the subscript *j* refers to each one of the 18 regions, *g* refers to gender, and *k* to the schooling level (se-secondary education, he-higher education) the individual *i* belongs to. *Y* are gross yearly wages and *X* are potential years of experience. Table 4 reports sample sizes used to estimate earnings equation (21) and (22).

Insert table 4 here

In table 2, we refer to model 1 when risk and return are calculated from equation (21), and we refer to model 2 when they are calculated from (22). We define the return as the ratio of lifetime earnings between individuals possessing higher education and secondary education calculated by gender and region

$$\mathrm{Re}\,turn_{jg} = \frac{\sum_{t=0}^{42} \hat{y}_{t,he} / (1+r)^t}{\sum_{t=0}^{47} \hat{y}_{t,se} / (1+r)^t} \tag{23}$$

where $\hat{y}$ are the estimated earnings from wage equation (21) or (22), *r=0.035* is a the discount rate, and the superscript *t* refers to years of experience. We define risk as the ratio of the variance of the estimated residuals between individuals possessing higher and secondary education

$$Risk_{jg} = \frac{\text{var}(\hat{\varepsilon}_{i,he})}{\text{var}(\hat{\varepsilon}_{i,se})} \tag{24}$$

where $\hat{\varepsilon}$ is the exponential of the estimated residual from equation (21) or (22). Finally, to allow for heterogeneous risk attitudes we use the following variable

$$Lottery_{ijg} = Risk_{jg} * D_i \tag{25}$$

where *D* is a dummy variable that takes 1 if the household *i* spends a given share of their incomes in gambling. The different shares of income expended in gambling are reported in table 5. Once Return, Risk and Lottery are estimated from earnings equations they are included as covariates in our probit schooling choice model.

Insert table 5 here

Appendix B (effect of measurement errors)

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 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, 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 GMM (see e.g. Hong and Tamer, 2003), or in minimum distance estimators as Li (2000) and Hsiao (1989). In this appendix, we 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 $\Sigma_Z = \text{var}(Z)$. According to equations written above $\Sigma_x = \Sigma_z - \Sigma_u$. Therefore, 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:

$$\beta_1 = \frac{\beta_0 \sigma_x^2}{\sqrt{\sigma_x^2 + \sigma_u^2}\sqrt{\sigma_x^2 + \sigma_u^2 + \beta_0 \sigma_x^2 \sigma_u^2}} \tag{26}$$

where σ_x^2 and σ_u^2 are the variance of the true regressor X and the measurement error u, respectively. In expression (26), β_0 is the true parameter and β_1 its inconsistent estimator. In absence of measurement error, that is u=0 and σ_u^2=0, β_0=β_1. Expression (26) suggests that the greater measurement error u, the greater σ_u^2. Therefore, the absolute value of β_0 will tend to be underestimated. Under 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 Σ_Z and the remaining variance is Σ_u. In order to assess the bias, we will make the following assumption

$$\begin{aligned} &\Sigma_Z = \Sigma_X + \Sigma_u = \alpha\Sigma_Z + (1-\alpha)\Sigma_Z \\ &\Sigma_X = \alpha\Sigma_Z \\ &\Sigma_u = (1-\alpha)\Sigma_Z \end{aligned} \tag{27}$$

With no 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 (26) that yields

$$\beta_0 = \frac{\beta_1(\sigma_x^2 + \sigma_u^2)\left(\beta_1\sigma_u^2 + \sqrt{\beta_1^2\sigma_u^4 + 4}\right)}{2\sigma_x^2} \tag{28}$$

As β_1 we take our probit estimations for return and risk in table 2. Under the presence of measurement errors, according to expression (28) and assumption (27), 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), the effect is modest, as table 6 shows.

Insert table 6 here

According to expression (26), a consistent estimator of β_0 can be achieved by applying the following transformation over Z (see Iwata, 1992)

$$\hat{X} = Z\hat{\Sigma}_Z^{-1}\hat{\Sigma}_X \quad (29)$$

Conventional probit estimation using (29) provides consistent estimators. To estimate $\hat{\Sigma}_X$ we use again assumption (27). The results are reported in table 7.

Insert table 7 here

In table 7 we also observe than not only the greater error measurement, the greater true value of the parameter, but also the greater variance. Both, estimated parameters and their variance rise at the same proportion, thus significance levels are unaffected.

References

Amemiya, Y. (1985). ‘Instrumental variables estimator for the nonlinear errors-in-variables model’, *Journal of Econometrics*, Vol. 28, pp. 273-290.

Baker, M. and Solon, G. (2003). ‘Earnings dynamics and inequality among Canadian men 1976-1992: evidence from longitudinal income tax records’, *Journal of Labor Economics*, Vol. 21, pp. 289-322.

Belzil, C. and Hansen, J. (2002). *Earnings Dispersion, Risk Aversion and Education*, IZA Discussion Paper 513, Bonn.

Chen, S. (2001). *Is Investing in College Education Risky?*, SUNY Working Paper, October, Albany.

Diaz-Serrano, L. (2001). *Human Capital, Progressive Taxation and Risk Aversion*, PhD Dissertation, Universitat Rovira i Virgili, Tarragona.

Eaton, J. and Rosen, H.S. (1980). ‘Taxation, human capital and uncertainty’, *American Economic Review*, Vol. 70, pp. 705-715.

Hartog, J., Ferrer-i-Carbonnell, A. and Jonker, N. (2002). ‘Linking measured risk aversion to individual characteristics’, *Kyklos*, Vol. 55, pp. 3-26.

Hartog, J., van Ophem, H. and Bajdechi, S. (2003). *How Risky is Investment in Human Capital?*, Working Paper, Universiteit van Amsterdam.

Hogan, V. and Walker, I. (2001). *Education Choice Under Uncertainty*, working paper University College Dublin/University of Warwick.

Hong, H. and Tamer, E. (2003). ‘A simple estimator for nonlinear error in variable models’, *Journal of Econometrics*, Vol. 117, 1-19

Hsiao, C. (1989). ‘Consistent estimation for some nonlinear errors-in-variables models’, *Journal of Econometrics*, Vol. 41, pp. 159-185.

Iwata, S. (1992). ‘Errors-in-variables regression using estimated latent variables’, *Econometric Reviews*, Vol. 11, pp. 195-200.

Iwata, S. (2001). ‘Recentered and rescaled instrumental variable estimation of tobit and probit models with errors in variables’, *Econometric Reviews*, Vol. 20, pp. 319-335.

Jacobs, B. (2002). *Public Finance and Human Capital*, PhD Dissertation, Universiteit van Amsterdam, Tinbergen Institute Research Series 280.

Kodde, D.A. (1986). ‘Uncertainty and the demand for education’, *Review of Economics and Statistics*, Vol. 68, pp. 460-467.

Levhari, D. and Weiss, Y. (1974). ‘The effect of risk on the investment in human capital’, *American Economic Review*, Vol. 64, pp. 950-963.

Li, T. (2000). ‘Estimation of nonlinear errors-in-variables models: A simulated minimum distance estimator’, *Statistics & Probability Letters*, Vol. 47, pp. 243-248.

Li, T. and Hsiao, C. (2003). ‘Robust estimation of generalized linear models with measurement errors’, *Journal of Econometrics*, forthcoming.

Williams, J. (1979). ‘Uncertainty and the accumulation of human capital over the lifecycle’, *Journal of Business*, Vol. 52, pp. 521-548.

TABLE 1

Return and risk by region and gender. Earnings functions estimated according to equation (21)-model 1 and equation (22)-model 2

Spanish Regions	*Model 1*				*Model 2*			
	Return		*Risk*		*Return*		*Risk*	
	Men	*Women*	*Men*	*Women*	*Men*	*Women*	*Men*	*Women*
1. Andalucia	1.556	1.859	0.341	0.470	1.532	1.963	0.341	0.470
2. Aragon	1.336	1.361	1.196	0.855	1.273	1.510	1.196	0.855
3. Asturias	1.277	1.365	0.912	1.274	1.328	0.759	0.912	1.274
4. Baleares	1.263	1.214	1.161	0.706	1.243	1.427	1.161	0.706
5. Canarias	1.632	1.726	0.449	0.584	1.648	2.112	0.449	0.584
6. Cantabria	1.748	1.262	0.804	1.484	1.733	1.712	0.804	1.484
7. Castilla-La Mancha	1.328	1.705	0.874	0.667	1.337	1.632	0.874	0.667
8. Castilla-Leon	1.585	1.751	0.759	0.438	1.559	2.034	0.759	0.438
9. Com. Valenciana	1.573	1.576	0.975	0.294	1.576	1.570	0.975	0.294
10. Catalunya	1.370	1.592	0.614	1.068	1.294	1.924	0.614	1.068
11. Extremadura	1.668	1.452	1.817	0.619	1.706	1.465	1.817	0.619
12. Galicia	1.503	1.564	0.319	0.530	1.509	1.632	0.319	0.530
13. Madrid	1.288	1.349	0.092	0.591	1.294	1.223	0.092	0.591
14. Murcia	1.509	1.475	0.621	4.167	1.457	1.365	0.621	4.167
15. Navarra	1.194	1.577	1.839	0.592	1.259	1.524	1.839	0.592
16. Pais Vasco	1.561	1.690	0.771	0.702	1.563	1.696	0.771	0.702
17. Rioja	1.575	1.910	1.880	1.442	1.450	2.405	1.880	1.442
18. Ceuta-Melilla	1.320	1.860	0.598	0.345	1.406	0.963	0.598	0.345

TABLE 2

Probit estimates of demand for higher education in Spain

	Model 1			*Model 2*		
	Coeff.	*Elasticity*	*Z-value*	*Coeff.*	*Elasticity*	*Z-value*
Constant	-4.0061		-4.75	-3.6437		-4.45
Return	0.6721	0.2534	3.46	0.3682	0.1389	2.94
Risk	-0.1365	-0.0515	-2.20	-0.0850	-0.0320	-1.76
Household variables						
Log(Household Income)	0.2169	0.0818	3.84	0.2160	0.0815	3.83
Log(Household size)	-0.5255	-0.1982	-5.01	-0.5312	-0.2003	-5.07
Home Ownership	0.1241	0.0472	1.94	0.1201	0.0457	1.88
Household head education						
Primary	0.2988	0.1131	3.61	0.2970	0.1124	3.59
Secondary	0.6612	0.2192	5.75	0.6628	0.2197	5.76
Degree (3-years college)	0.9894	0.2927	6.68	0.9702	0.2889	6.56
Bachelor	1.3107	0.3512	8.05	1.3100	0.3512	8.03
Household head occupation						
Manager (farming)	0.3667	0.1284	2.72	0.3619	0.1269	2.69
Blue-Collar (farming)	-0.1005	-0.0385	-0.63	-0.0969	-0.0371	-0.60
Professionals (Ind.-Serv.)	0.1734	0.0639	2.21	0.1703	0.0628	2.17
Manager (Ind.-Serv.)	0.4642	0.1623	3.97	0.4704	0.1643	4.01
White-Collar (Ind.-Serv.)	0.2896	0.1052	3.79	0.2904	0.1055	3.80
Not classified occupation	0.4242	0.1454	1.91	0.4167	0.1431	1.89
City size						
10.000-50.000	-0.4013	-0.1564	-1.89	-0.4114	-0.1604	-1.95
50.000-100.000	-0.4662	-0.1782	-2.25	-0.4828	-0.1845	-2.34
100.000-500.000	-0.4371	-0.1704	-2.05	-0.4279	-0.1668	-2.01
>500.000	-0.1123	-0.0428	-1.23	-0.1165	-0.0444	-1.28
Urbanization	0.4861	0.1853	2.61	0.4991	0.1903	2.69
Job seeking	0.1490	0.0562	1.86	0.1717	0.0648	2.15
Log-likelihood		-1462.40			-1464.92	
Wald test		332.51			331.17	
Sample size		2501			2501	

Note: Probit estimates include dummies for region that are significant at 5% level or better. Model 1: Return and risk variables estimated from equation (21); model 2: Return and risk estimated from equation (22).

TABLE 3

Probit estimates of demand for higher education controlling for heterogeneous attitudes towards risk

	Model 1			*Model 2*		
	Coefficient	*Elasticity*	*z-value*	*Coefficient*	*Elasticity*	*z-value*
Return	0.6699	0.2526	3.45	0.3665	0.1382	2.93
Risk	-0.1282	-0.0483	-1.87	-0.0783	-0.0295	-1.42
Lottery (1%)	-0.0185	-0.0070	-0.28	-0.0136	-0.0051	-0.23
Return	0.6828	0.2575	3.51	0.3758	0.1417	3.00
Risk	-0.1695	-0.0639	-2.64	-0.1152	-0.0435	-2.28
Lottery (2%)	0.1140	0.0430	1.53	0.0953	0.0360	1.43
Return	0.6729	0.2537	3.46	0.3697	0.1394	2.95
Risk	-0.1693	-0.0638	-2.63	-0.1161	-0.0438	-2.28
Lottery (3%)	0.1806	0.0681	2.15	0.1649	0.0622	2.22
Return	0.6712	0.2530	3.45	0.3685	0.1390	2.94
Risk	-0.1663	-0.0627	-2.60	-0.1136	-0.0428	-2.25
Lottery (4%)	0.1829	0.0690	1.96	0.1685	0.0635	2.08
Return	0.6671	0.2515	3.43	0.3651	0.1377	2.91
Risk	-0.1474	-0.0556	-2.34	-0.0939	-0.0354	-1.90
Lottery (5%)	0.1592	0.0600	1.37	0.1295	0.0488	1.24

Note: Probit estimates include dummies for region that are significant at 5% level or better. Model 1: return and risk variables estimated from equation (21); model 2: return and risk estimated from equation (22).
Variable lottery defined in equation (25)

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TABLE 4

Sample sizes for the estimation of the earnings functions (21) and (22)

Spanish Regions	*Men*		*Women*	
	Secondary	*University*	*Secondary*	*University*
1. Andalucia	409	266	209	163
2. Aragon	155	98	95	70
3. Asturias	68	33	34	14
4. Baleares	75	20	47	24
5. Canarias	118	60	63	39
6. Cantabria	67	29	40	17
7. Castilla-La Mancha	385	253	205	210
8. Castilla-Leon	176	109	75	103
9. Com. Valenciana	306	168	183	94
10. Catalunya	200	117	129	75
11. Extremadura	67	52	34	40
12. Galicia	219	105	117	94
13. Madrid	152	98	81	64
14. Murcia	70	31	35	27
15. Navarra	78	44	40	27
16. Pais Vasco	288	159	135	124
17. Rioja	56	47	28	24
18. Ceuta y Melilla	37	9	9	7
Total	2,926	1,698	1,559	1,216

TABLE 5

Number of individuals with a given % of yearly income spent in lotteries

	% household income spent in gambling				
	1%	*2%*	*3%*	*4%*	*5%*
# of individuals (sample size=2501)	810	517	337	239	180
% of the sample (sample size=2501)	32.4	20.7	13.5	9.6	7.2

TABLE 6

Estimates of β_0, true value of the parameter, in expression (28) for different values of α in expression (27)

	Model 1		*Model 2*	
α	*Return*	*Risk*	*Return*	*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: For α=1 estimated parameters coincide with our estimates in table 2. Model 1: return and risk variables estimated from equation (21); model 2: return and risk estimated from equation (22).

TABLE 7

Probit estimates of demand for education in Spain applying transformed regression defined in expression (29) for different values of α in expression (27)

	Model 1				*Model 2*			
	Return		*Risk*		*Return*		*Risk*	
α	*Coeff.*	*Z-value*	*Coeff.*	*Z-value*	*Coeff.*	*Z-value*	*Coeff.*	*Z-value*
1	0.6721	3.46	-0.1365	-2.20	0.3682	2.94	-0.0850	-1.76
0,9	0.7467	3.46	-0.1516	-2.20	0.4092	2.94	-0.0945	-1.76
0,8	0.8401	3.46	-0.1706	-2.20	0.4603	2.94	-0.1062	-1.76
0,7	0.9600	3.46	-0.1949	-2.20	0.5261	2.94	-0.1214	-1.76
0,6	1.1201	3.46	-0.2275	-2.20	0.6138	2.94	-0.1416	-1.76
0,5	1.3441	3.46	-0.2729	-2.20	0.7365	2.94	-0.1699	-1.76

Note: Model 1: return and risk variables estimated from equation (21); model 2: return and risk estimated from equation (22). We use the same variables than in table 2, the rest of coefficients remain unaltered.