# Earnings risk and demand for higher education: a cross-section test for Spain

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# EARNINGS RISK AND DEMAND FOR HIGHER EDUCATION:

# A CROSS-SECTION TEST FOR SPAIN

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Keywords: earnings risk, schooling decisions

JEL : I21

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 strong and the covariance between depreciation and production of human capital is highly negative.

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

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.

$$Y_{st} = ?_{st} Y_s \tag{1}$$

where $Y_{st}$ is earnings at age t for given schooling length s, $Y_s$ is a non-stochastic shift parameter and $?_{st}$ is a stochastic variable.[2] For a start, simplify to $?_{st} = ?_s$ and

$$\begin{aligned} &E(?_s) = 1 \\ &E\{?_s - E(?_s)\}^2 = s_s^2 \end{aligned} \tag{2}$$

$?_s$ 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 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

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[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.

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

$$
\begin{aligned}
W &= E\int_s^{\infty} U\{?_s Y_s\} e^{-rt}\, dt \\
&= \frac{1}{?} e^{-rs}\, E[U(?_s Y_s)]
\end{aligned}
\tag{3}
$$

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

$$
\begin{aligned}
E[U(?_s Y_s)] &= E[U(Y_s)] + Y_s U^{'}(Y_s) E(?_s - 1) + \frac{1}{2} Y_s^2 U^{''}(Y_s) E(?_s - 1)^2 \\
&= U(Y_s) + \frac{1}{2} Y_s^2 U^{''}(Y_s) s_s^2
\end{aligned}
\tag{4}
$$

Then, rewrite the objective function as

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

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

$$
\mathrm{e}_s \left\{ \mu_s - \mathrm{a}_s s_s^2 \left( \mu_s + ?_s - \frac{1}{2} ? \right) \right\} - ? = 0 \tag{6}
$$

with

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

$$?_s = \frac{\partial s_s}{\partial s}\frac{1}{s_s} \tag{8}$$

$$a_s = \frac{U''(Y_s)}{-U'(Y_s)}Y_s \tag{9}$$

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

Hence, $\mu_s$ is the marginal rate of return to schooling, $?_s$ is the relative gradient of risk to schooling, $a_s$ is relative risk aversion and $e_s$ is the income elasticity of utility. To understand this expression, note

- if $s_s^2 = \frac{\partial s_s}{\partial s} = 0$ and $e_s = 1$, 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 $s_s^2 = \frac{\partial s_s}{\partial s} = 0$ and $e_s \neq 1$, we have the modification of utility maximization rather than earnings maximization.
- if individuals are risk neutral $(a_s = 0)$ we have the same result as when there is no risk $(s_s^2 = 0, all\ s)$.[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 zero-axis and is shifted to the right), and anything that shifts the curve down reduces optimum schooling.

[3] Note that $a_s = 0$ implies U"= 0, hence U' is constant, or $e_s = 1$.

Effects of risk on demand for education length depend crucially on risk attitude $a_s$ and on the term in the inner brackets. If this term is positive $\left(\mu_s + ?_s > \frac{1}{2}?\right)$, an increase in risk, at constant risk gradient, will reduce optimum schooling for risk averters $(a_s > 0)$ and increase it for risk lovers. However, if risk strongly falls with education $\left(?_s < \frac{1}{2}? - \mu_s\right)$ 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 $\mu_s$ interacts with risk attitude. An increase in returns will only increase optimum schooling length if $a_s < 1/s_s^2$. 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 *Generalisation*

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 $?_{st}Y_{st}$ where $Y_{st}$ is non-stochastic and $?_{st}$ is the stochastic shock at age t, for given education s, with

$$E\left(?_{st}\right) = 1 \quad , \quad all\ s, t \tag{11}$$

$$E\left\{?_{st} - E\left(?_{st}\right)\right\}^2 = \mathrm{s}_{st}^{\,2} \tag{12}$$

$$E\left\{?_{st} - E\left(?_{st}\right)\right\}\left\{?_{sv} - E\left(?_{sv}\right)\right\} = 0 \quad , t \neq v \tag{13}$$

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

$$\begin{aligned} \mathrm{W} &= \mathrm{E}\int_s^\infty E\left\{?_{st} Y_{st}\right\} e^{-rt}\, dt \\ &= \int_s^\infty e^{-rt} E\left\{U\left(?_{st} Y_{st}\right)\right\} dt \end{aligned} \tag{14}$$

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

$$\mathrm{W} = \int_{\mathrm{s}}^\infty e^{-rt}\left[U\left(Y_{st}\right) + \frac{1}{2} U^{''}\left(Y_{st}\right) Y_{st}^2\, \mathrm{s}_{st}^{\,2}\right] dt \tag{15}$$

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

$$\begin{aligned} \frac{\partial \mathrm{W}_s}{\partial s} &= -\left[\boldsymbol{e}_{ss}^{-1} - \frac{1}{2}\mathrm{a}_{ss}\, \mathrm{s}_{ss}^{\,2}\right] U_{ss}^{'} Y_{ss} e^{-rs} + \\ &+ \int_s^\infty \left[\mu_{st} - \mathrm{a}_{st}\, \mathrm{s}_{st}^{\,2}\left(\mu_{st} + ?_{st}\right)\right] U_{st}^{'} Y_{st} e^{-rt}\, dt = 0 \end{aligned} \tag{16}$$

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

$$?_{st} = \frac{\partial \mathrm{s}_{st}}{\partial s}\frac{1}{\mathrm{s}_{st}} \tag{18}$$

$$\mathrm{a}_{st} = \frac{U^{''}\left(Y_{st}\right)}{-U^{'}\left(Y_{st}\right)} Y_{st} \tag{19}$$

$$\boldsymbol{e}_{st} = \frac{\partial U\left(Y_{st}\right)}{\partial Y_{st}}\frac{Y_{st}}{U\left(Y_{st}\right)} > 0 \tag{20}$$

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 $a_{st}$, from risk aversion to risk loving, switches the sign of the effect of changes in variance $s^2_{st}$ and in risk gradient $?_{st}$. A change in $s^2_{ss}$, 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 $(\mu_{st} + ?_{st} < 0)$. 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 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

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

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 for the two educations. Both are measured at the level of an individual's region of residence.

In the Spanish system of education in 1990, compulsory primary education is 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 is 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 is 20-21 and the long degree 22-23.

Our data source is the Spanish Family Budget Survey EPF 1990/91, a nationally representative survey among 21155 households, collecting information on all 72123 individual household members. We use the database to estimate earnings functions separately for university and secondary education in an individual's region of residence, 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)[5]. There are 18 Autonomous Regions in Spain. 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[6]. Table 1 gives basic information on returns and risk. The total sample size for the earnings functions is 7400; region 18, Ceuta-Mellilla, is located in Morocco and has rather few observations. To estimate earnings functions for

[5] 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).

university educated, we use workers possessing the short and the long degree, since both are higher education. From the 2914 individuals in our sample possessing a higher education, 1619 had a short degree (3 years college) and 1295 had a bachelor (long degree – 5 years college).

The resulting estimates of returns and risk, counterparts to $m$ and $g$ 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 $\gamma$ below 1 dominate, with a lower earnings risk for university than for secondary education.

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 is attending schooling leading to a short or a long degree. In the sample of youth, most of them are attending the long degree. There are 1521 individuals attending higher education, 400 attending the short degree and 1121 attending the long degree. The endogenous variable takes on 0 if individuals have completed secondary education and are working. These 980 individuals are not attending any sort of higher education. Among the total sample of 2501 observations, 1277 are male and 1224 are female. We only include individuals in the youth sample if they are registered as member of the parental household (sons and daughters). It is

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

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.

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.

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). 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.[7] The differences between Model 1 and Model 2 are not substantial.

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

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 10%. 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..

*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. As we needed information on parental background, we have restricted our youth sample to "sons and daughters", 92.12% of the individuals aged 17-23 in our sample. This means that we have excluded 54 household heads, 50 spouses, 77 other relatives of the household and 33 non-relatives. 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 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. Presumably, such expenditures reflect risk attitudes in the household. We created dummies to pick out households who spend more than x% of the family budget annually on lottery tickets, with x running from 1 to 6. As Appendix A (table 5) shows, the sample share so selected decreases from 32.4 to 5.5 %. 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 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. This is strong support for one of our key predictions, i.e. a pivotal role for risk attitudes.

## 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 a Mincer wage equation as

$$Y_{ijk} = a_{jk} + b_{jk} X_{ijk} + d_{jk} X_{ijk}^{2} + g_{jk} G_{jk} + u_{ijk} \tag{21}$$

and

$$Y_{ijkg} = a_{jkg} + b_{jkg} X_{ijkg} + d_{jkg} X_{ijkg}^{2} + u_{ijkg} \tag{22}$$

where the subscript $j$ refers to each of the 18 regions, $g$ refers to gender, and $k$ is the schooling level (se-secondary education, he -higher education) the individual $i$ belongs to. Y are gross yearly wages and X are years of experience. Table 4 reports sample sizes used to estimate earnings equation (21) or (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 (21) or (22), $r=0.035$ is a the discount rate, and the subscript t refers to years of experience. We define risk as the ratio of the variance of the estimated residuals between individuals possessing higher education and those possessing secondary education

$$Risk_{jg} = \frac{\mathrm{var}(\hat{e}_{ihe})}{\mathrm{var}(\hat{e}_{ise})} \tag{24}$$

where $\hat{e}$ 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 devoted to 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 $y = X b_0 + e$ , where y can be an observed or latent variable, $X$ contains the exogenous variables and e a random error term. The problem arises when instead of $X$ we observe Z, being $Z = X + u$ , and u the associated measurement error. So, when we estimate $y = Z b_0 + e$ , we have that $y = X b_0 - u b_0 + e$ . Then, OLS for the linear regression model, and ML estimation in the case of the probit will provide a biased estimation of *ß0* (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 consist 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 the minimum distance estimators as Li (2000) and Hsiao (1989). In this appendix, we use two different ways to assess the possible consequences of measurement errors. They generate the same results and we conclude that the impact is fairly modest.

Define $s_e^2$, $\Sigma_u = \mathrm{var}(u)$ , $\Sigma_x = \mathrm{var}(x)$ , and $\Sigma_z = \mathrm{var}(z)$ . Hence, according to equations written above we have that $\Sigma_x = \Sigma_z - \Sigma_u$ . So, the variance of the true exogenous variables $X$ depends on the variance of the measurement error u, which is unknown. This lack of knowledge of $S_u$ implies some identification problems that lead to an inconsistent estimation of *ß0* when we apply the traditional ML estimation When the measurement error problem is ignored, the inconsistent estimation of *ß0* will converge to the following expression:

$$\beta_1 = \frac{\beta_0 \sigma_x^2}{\sqrt{\sigma_x^2 + \sigma_u^2}\sqrt{\sigma_x^2 + \sigma_u^2 + \beta_0 \sigma_x^2 \sigma_u^2}} \qquad (26)$$

where $s_x^2$ and $s_u^2$ are the variance of the true regressor $X$ and the measurement error $u$ respectively. In expression (26) $ß_0$ would be the true parameter and $ß_1$ the inconsistent estimator. In absence of measurement error ($u$=0 and $s_u^2$=0) we have that expression (26) becomes $ß_0$ ($ß_0$=$ß_1$), which means that the traditional ML estimation of $ß_0$ will converge to its true value. Thus, the bias will crucially depend on the unknown value of $s_u^2$, since as mentioned previously $s_x^2 = s_z^2 - s_u^2$. Expression (26) clearly suggests that as the measurement error $u$ increases, and hence also $s_u^2$, the absolute value of $ß_0$ 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 matrix of $Z$ takes the following form $\Sigma_z = \Sigma_x + \Sigma_u$. We do not know which part of the variance is due to $X$ and $u$, but we know that due to a measurement error a share of the variance of $Z$ (known) is in $\Sigma_x$ and the remaining variance is in $\Sigma_u$. In order to assess the bias, we will make the following assumption

$$\begin{aligned}
\Sigma_z &= \Sigma_x + \Sigma_u = a\Sigma_Z + (1-a)\Sigma_Z \\
\Sigma_x &= a\Sigma_Z \\
\Sigma_u &= (1-a)\Sigma_z
\end{aligned} \qquad (27)$$

In the absence of measurement errors ($a$=1), we have that the variance of the true variable $X$ coincides with the variance of what we observe $Z$.

According to expression (26), to know the bias we just have to develop this expression and we have

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

As *ß₁* we will take our probit estimations. Under the existence of measurement errors, according to expression (28) and assumption (27), we know that the theoretical true value of *ß₀* should depend on $a$. 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 $a$=0.7. Then, compared to the interpretation of no measurement errors ($a$=1.0), the effect is modest, as the table 6 shows.

Insert table 6 here

Another way to asses the bias due to measurement errors can be found in Iwata (1992). This method consists of applying the following transformation to Z (potentially measured with error)

$$\hat{X} = Z\hat{\Sigma}_z^{-1}\hat{\Sigma}_x \tag{29}$$

When we apply transformation (29) to the observed variables, and we replace Z by $\hat{X}$ in our model, the estimation of the parameters in the usual way provides consistent estimates. This method is valid for linear regression and probit. To estimate $\hat{\Sigma}_x$ we use again assumption (27). The results are reported in table 7.

Insert table 7 here

Indeed, we obtain exactly the same results. From table 7 we also observe than not only the true value of the parameter but also its variance increases as the measurement error assumed increases. This implies that significance levels are unaffected.

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

| | Model 1 | | | | **Model 2** | | | |
|---|---|---|---|---|---|---|---|---|
| | **Return** | | **Risk** | | **Return** | | **Risk** | |
| **Region** | **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. Aragons | 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 y Melilla | 1,320 | 1,860 | 0,598 | 0,345 | 1,406 | 0,963 | 0,598 | 0,345 |

**Table 2**: Probit estimations for demand for higher education

| | Model 1 | | | Model 2 | | |
|---|---|---|---|---|---|---|
| | **Coef.** | **dF(x)/dx** | **z-value** | **Coef.** | **dF(x)/dx** | **z-value** |
| Constant | -3,8204 | | -4,59 | -3,5882 | | -4,43 |
| **Return** | **0,4781** | **0,1804** | **2,87*** | **0,2946** | **0,1112** | **2,63*** |
| **Risk** | **-0,1073** | **-0,0405** | **-1,90***** | **-0,0773** | **-0,0292** | **-1,74***** |
| Log(Household Income) | 0,2070 | 0,0781 | 3,70 | 0,2043 | 0,0771 | 3,66 |
| Log(Household size) | -0,5233 | -0,1975 | -5,04 | -0,5221 | -0,1970 | -5,04 |
| Home Ownership | 0,1147 | 0,0436 | 1,82 | 0,1129 | 0,0429 | 1,79 |
| *Household head education* | | | | | | |
| Primary | 0,3319 | 0,1257 | 4,09 | 0,3284 | 0,1244 | 4,05 |
| Secondary | 0,6996 | 0,2300 | 6,19 | 0,7002 | 0,2302 | 6,19 |
| Degree (3-years college) | 1,0365 | 0,3025 | 7,11 | 1,0226 | 0,2998 | 7,01 |
| Bachelor | 1,3445 | 0,3568 | 8,38 | 1,3458 | 0,3571 | 8,38 |
| *Household head occupation* | | | | | | |
| Manager (farming) | 0,4210 | 0,1456 | 3,16 | 0,4186 | 0,1449 | 3,15 |
| Blue-Collar (farming) | -0,1247 | -0,0479 | -0,77 | -0,1230 | -0,0472 | -0,76 |
| Professionals (Ind.-Serv.) | 0,1927 | 0,0709 | 2,47 | 0,1868 | 0,0688 | 2,40 |
| Manager (Ind.-Serv.) | 0,4675 | 0,1636 | 4,06 | 0,4745 | 0,1658 | 4,11 |
| White-Collar (Ind.-Serv.) | 0,3198 | 0,1158 | 4,23 | 0,3191 | 0,1156 | 4,22 |
| Not classified occupation | 0,4635 | 0,1572 | 2,10 | 0,4599 | 0,1562 | 2,10 |
| *City size* | | | | | | |
| 10.000-50.000 | -0,4400 | -0,1717 | -2,32 | -0,4313 | -0,1683 | -2,28 |
| 50.000-100.000 | -0,3940 | -0,1506 | -2,23 | -0,3783 | -0,1445 | -2,15 |
| 100.000-500.000 | -0,3412 | -0,1326 | -1,82 | -0,3086 | -0,1197 | -1,66 |
| >500.000 | -0,1527 | -0,0584 | -1,72 | -0,1571 | -0,0601 | -1,77 |
| Urbanization | 0,4019 | 0,1533 | 2,53 | 0,3872 | 0,1476 | 2,45 |
| Job seeking | 0,1955 | 0,0738 | 2,51 | 0,2190 | 0,0826 | 2,84 |
| Log likelihood | -1479 | | | -1480 | | |
| Wald test | 318 | | | 316 | | |
| Sample size | 2501 | | | 2501 | | |

*Significant at 1% level
**Significant at 5% level
***Significant 10% level

**Table 3:** Probit estimation for demand for higher education with Gambling

| | Model 1 | | | Model 2 | | |
|---|---|---|---|---|---|---|
| | **Coef.** | **dF(x)/dx** | **z-value** | **Coef.** | **dF(x)/dx** | **z-value** |
| Return | 0,4779 | 0,1803 | 2,87* | 0,2946 | 0,1112 | 2,63* |
| Risk | -0,1046 | -0,0395 | -1,67*** | -0,0768 | -0,0290 | -1,51 |
| Lottery (1%) | -0,0063 | -0,0024 | -0,10 | -0,0009 | -0,0004 | -0,02 |
| Return | 0,4826 | 0,1821 | 2,89* | 0,2996 | 0,1131 | 2,67* |
| Risk | -0,1400 | -0,0528 | -2,39* | -0,1088 | -0,0411 | -2,34* |
| Lottery (2%) | 0,1219 | 0,0460 | 1,64*** | 0,1048 | 0,0396 | 1,57 |
| Return | 0,4742 | 0,1789 | 2,84* | 0,2940 | 0,1109 | 2,62* |
| Risk | -0,1380 | -0,0521 | -2,35* | -0,1074 | -0,0405 | -2,26** |
| Lottery (3%) | 0,1798 | 0,0679 | 2,15** | 0,1673 | 0,0631 | 2,29** |
| Return | 0,4722 | 0,1782 | 2,83* | 0,2921 | 0,1102 | 2,60* |
| Risk | -0,1347 | -0,0508 | -2,32* | -0,1042 | -0,0393 | -2,25** |
| Lottery (4%) | 0,1778 | 0,0671 | 1,91*** | 0,1662 | 0,0627 | 2,06** |
| Return | 0,4743 | 0,1790 | 2,84* | 0,2916 | 0,1100 | 2,60* |
| Risk | -0,1196 | -0,0451 | -2,08** | -0,0872 | -0,0329 | -1,92** |
| Lottery (5%) | 0,1658 | 0,0626 | 1,43 | 0,1345 | 0,0507 | 1,30 |
| Return | 0,4785 | 0,1806 | 2,87* | 0,2947 | 0,1112 | 2,62* |
| Risk | -0,1136 | -0,0429 | -2,00** | -0,0823 | -0,0310 | -1,84*** |
| Lottery (6%) | 0,1494 | 0,0564 | 1,09 | 0,1177 | 0,0444 | 0,95 |

*Significant at 1% level
**Significant at 5% level
***Significant 10% level

**Table 4:** Sample sizes for the estimation of the earnings functions (21)-model 1 and (22)-model 2.

| | Model 1 | | Model 2 | | | |
|---|---|---|---|---|---|---|
| | | | Men | | Women | |
| **Region** | **Secondary** | **University** | **Secondary** | **University** | **Secondary** | **University** |
| 1. Andalucia | 618 | 429 | 409 | 266 | 209 | 163 |
| 2. Aragons | 250 | 168 | 155 | 98 | 95 | 70 |
| 3. Asturias | 102 | 47 | 68 | 33 | 34 | 14 |
| 4. Baleares | 122 | 44 | 75 | 20 | 47 | 24 |
| 5. Canarias | 181 | 99 | 118 | 60 | 63 | 39 |
| 6. Cantabria | 107 | 46 | 67 | 29 | 40 | 17 |
| 7. Castilla-La Mancha | 590 | 463 | 385 | 253 | 205 | 210 |
| 8. Castilla-Leon | 251 | 212 | 176 | 109 | 75 | 103 |
| 9. Com. Valenciana | 489 | 262 | 306 | 168 | 183 | 94 |
| 10. Catalunya | 329 | 192 | 200 | 117 | 129 | 75 |
| 11. Extremadura | 101 | 92 | 67 | 52 | 34 | 40 |
| 12. Galicia | 336 | 199 | 219 | 105 | 117 | 94 |
| 13. Madrid | 233 | 162 | 152 | 98 | 81 | 64 |
| 14. Murcia | 105 | 58 | 70 | 31 | 35 | 27 |
| 15. Navarra | 118 | 71 | 78 | 44 | 40 | 27 |
| 16. Pais Vasco | 423 | 283 | 288 | 159 | 135 | 124 |
| 17. Rioja | 84 | 71 | 56 | 47 | 28 | 24 |
| 18. Ceuta y Melilla | 46 | 16 | 37 | 9 | 9 | 7 |

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

| % of the household income spent in gambling | 1% | 2% | 3% | 4% | 5% | 6% |
|---|---|---|---|---|---|---|
| # of individuals (sample size=2501) | 810 | 517 | 337 | 239 | 180 | 138 |
| % of the sample (sample size=2501) | 32,4 | 20,7 | 13,5 | 9,6 | 7,2 | 5,5 |

**Table 6**: Effect of measurement error according to (28)

| | Model 1 | | Model 2 | |
|---|---|---|---|---|
| **a** | **$\beta_0$(return)** | **$\beta_0$(risk)** | **$\beta_0$(return)** | **$\beta_0$(risk)** |
| 1.0 | 0.4781 | -0.1073 | 0.2946 | -0.0773 |
| 0.9 | 0.5316 | -0.1190 | 0.3277 | -0.0857 |
| 0.8 | 0.5984 | -0.1337 | 0.3690 | -0.0963 |
| 0.7 | 0.6844 | -0.1526 | 0.4221 | -0.1099 |
| 0.6 | 0.7990 | -0.1778 | 0.4929 | -0.1281 |
| 0.5 | 0.9595 | -0.2131 | 0.5921 | -0.1534 |

**Table 7**: Effects of measurement error using expression (29).

| | | Model 1 | | Model 2 | |
|---|---|---|---|---|---|
| **a** | | **Coef.** | ***z*-val.** | **Coef.** | ***z*-val.** |
| 1 | Return | 0,4781 | 2,87 | 0,2946 | 2,63 |
| | Risk | -0,1073 | -1,90 | -0,0773 | -1,74 |
| 0,9 | Return | 0,5312 | 2,87 | 0,3274 | 2,63 |
| | Risk | -0,1192 | -1,90 | -0,0859 | -1,74 |
| 0,8 | Return | 0,5976 | 2,87 | 0,3683 | 2,63 |
| | Risk | -0,1341 | -1,90 | -0,0966 | -1,74 |
| 0,7 | Return | 0,6829 | 2,87 | 0,4209 | 2,63 |
| | Risk | -0,1532 | -1,90 | -0,1104 | -1,74 |
| 0,6 | Return | 0,7968 | 2,87 | 0,4911 | 2,63 |
| | Risk | -0,1788 | -1,90 | -0,1288 | -1,74 |
| 0,5 | Return | 0,9561 | 2,87 | 0,5893 | 2,63 |
| | Risk | -0,2145 | -1,90 | -0,1545 | -1,74 |