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IS THERE A RISK-RETURN TRADE-OFF IN EDUCATIONAL CHOICES? EVIDENCE FROM SPAIN

LUIS DÍAZ-SERRANO
Universitat Rovira i Virgili, IZA
JOOP HARTOG
FEE-SCHOLAR, Universiteit van Amsterdam

We use data from Spain to test for an effect of earnings variance and skewness on individual wages. We carry out separate estimations for men and women. In accordance with the scant previous evidence mainly focused on the US, we report the existence of a risk-return trade-off across educational choices in the Spanish labor market. These results are in conformity with preferences of risk-averse individuals with decreasing absolute risk aversion and hence, with preference for skewness. In contrast with the previous literature, our analysis is based just in education cells, instead of on occupation or occupation/education cells. This improvement allows us to capture in a more suitable way the essence of earnings risk.

Keywords: Risk-aversion, skewness affection, educational choices, compensating wage differentials.

(*JEL* J3, D8)

1. Introduction

In a riskless world, deciding to pursue further education or what type of education to attend should be, undoubtedly, an easier task. In such a case, as the traditional human capital theory suggests, individuals would base their choice on earnings maximization, allowing for non-pecuniary elements as they may wish. However, in a risky world like ours, where the fact that workers are averse to unpredictable fluctuations in their incomes is universally recognized, such a decision becomes much more complicated. Economic theory suggests that uncertainty of future earnings, as an unattractive feature of any choice,

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should be compensated. In the empirical literature on compensating wage differentials there exists a wide variety of studies analyzing the effect of different sources of risk in the work place on wages. However, this literature is mainly focused on injury or fatality risks. Following Adam Smith we claim that in a competitive labor market there must exist a way of compensation in those career choices that entail a higher probability of failure (i.e. higher variance in earnings) in order to attract sufficient supply. While uncertainty in labor income is accounted for in theoretical models it has been rarely tested.

We will measure risk by the variance of earnings attached to an educational choice. Additionally, there is also a growing literature that shows the relevance of the skewness of the returns in many economic decisions. From a theoretical point of view, Tsiang (1974) argues that individuals have a preference for skewness, in addition to dispersion-aversion, in any economic decision involving an uncertain outcome. The empirical studies of Garret and Sobel (1999) and Golec and Tamarking (1998) observe that risk-averse individuals playing lottery games and betting in horse races in the US base their participation decision on the skewness of the respective prize distributions. Prackash et al. (2003) find empirical evidence from Latin American, US and European capital markets that investors do trade expected return of the portfolio for skewness. Díaz-Serrano (2004) empirically supports that positive skewness favors homeownership in Germany and Spain.

In the context of labor economics, the literature on risk compensation starts with King (1974). He observes a positive effect for variance and a negative effect for skewness in mean labor earnings, with the variance and skewness of earnings being computed and aggregated by occupation cells. As a first attempt, King's results are quite revealing; however, the empirical strategy he uses is affected by several econometric problems, since aggregating the data by occupation cells does not allow to control for many individual effects crucial in order to explain labor earnings. McGoldrick (1995) builds on King's work and using US microdata obtains the same results[1]. More recently, Hartog and Vijverberg (2002) in the US and Díaz-Serrano, Hartog and Nielsen (2003) in Denmark show that individuals appreciate positively skewed income distributions, and they incorporate this information into their

[1] Similar studies in the US context providing identical results regarding the effect of the variance on earnings are Feinberg (1981) and McGoldrick and Robst (1996).

occupational and educational choices[2]. In this paper, we empirically test for the Spanish labor market whether risk-averse workers are compensated for earnings risks in their educational choices, and whether there is a willingness to pay for positive skewness in their incomes.

We observe a positive effect of income risk on earnings, whereas the effect of skewness is negative. This result is the one observed in the previous literature and the one expected a priori. In this study we contribute to the previous literature in several aspects. Firstly, as in Díaz-Serrano, Hartog and Nielsen (2003) our estimates of the risk and skewness measures are based just on education cells instead of occupation or occupation/education cells. This strategy (education cells) is preferable over the one adopted in the previous literature (occupation or occupation/education cells). Although the studies mentioned above conciliate economic theory with the empirical evidence they fail, with the exception of Díaz-Serrano, Hartog and Nielsen (2003), to catch the inescapable risk associated with schooling choices instead of occupational choices: i.e. workers can switch occupations, whereas they cannot switch education as the earnings draw turns to be unfavourable. However, available data with enough education cells to allow for sufficient variability in the variance and skewness of earnings are very scarce. In this respect, as we do here, estimating risk and skewness just by education cells constitutes in itself a substantial improvement over the small previous literature. Secondly, we address the problem derived from clustering observations by education groups and from using generated regressors when estimating the effect of earnings risk and skewness on wages, which has been omitted in all the previous studies. And thirdly, we provide new evidence using Spanish data, which can be seen as a welcome addition to the previous empirical evidence from Denmark[3].

The remainder of the paper is structured as follows. Section 2 presents the theoretical background. In Section 3 we describe the empirical framework. In Section 4 we describe the dataset. We carry out the

[2] In Hartog and Vijverberg (2002) variance and skewness of earnings are estimated using occupation/education cells, whereas in Díaz-Serrano, Hartog and Nielsen (2003) variance and skewness of income is for the first time estimated using just education cells.

[3] Our results can only be directly compared with the ones provided in Díaz-Serrano, Hartog and Nielsen (2003) for Denmark, since this is the unique previous study that uses only education cells.

empirical analysis in Section 5. And section 6 summarizes and concludes.

2. Theoretical background

Tsiang (1974) found theoretical support for the claim that risk-averse individuals should display preference for skewness, in addition to aversion to dispersion (risk). Assuming that increasing absolute risk aversion is absurd, and hence requiring decreasing absolute risk aversion implies that individuals appreciate higher moments as e.g. skewness. Other well established theories also emphasize this conclusion. For example, prospect theory (Kahneman and Tversky, 1979, 1991) states that the individual's disutility caused by a loss is greater than the utility caused by a gain of the same size, which goes in the same direction as Tsiang's findings. These arguments suggest that if we assume future earnings attached to an educational choice to be uncertain, both the variance and skewness of earnings, in addition to the mean, should be considered when analyzing how these choices are planned and achieved. Hence, a natural extension would be the following hypothesis: if we assume earnings variability as an unattractive feature of any economic choice, this should be compensated in order to attract sufficient supply. Analogously, if we assume positive skewness as an attractive feature there should be a willingness to pay for it.

To understand how such a compensation mechanism in wages may arise we follow Hartog and Vijvenberg (2002) and Díaz-Serrano, Hartog and Nielsen. (2003). Assume that a risk-averse individual has to choose between two levels or types of education that only differ with respect to uncertainty. In the *certain* alternative, annual earnings are given by Y_f, generating utility $U(Y_f)$, where $U()$ is a concave utility function with $U' > 0, U'' < 0$ and $U''' > 0$ (as noted the latter condition is necessary for declining absolute risk aversion, see Tsiang, 1974 or Hartog and Vijverberg, 2002). In the *uncertain* option, income is a single draw for the rest of the working life, written as $Y_r + \varepsilon$. Equal expected lifetime utility (which characterises equilibrium in a competitive market with identical individuals) requires

$$\int_0^T U\left(Y_f\right) e^{-\delta t} dt = E \int_0^T U\left(Y_r + \varepsilon\right) e^{-\delta t} dt \qquad [1]$$

where T is the length of working life and δ the time discount rate. We can write the left-hand side as

$$\int_0^T U(Y_f)\,e^{-\delta t}dt = \frac{1}{\delta}\left(1 - e^{-\delta T}\right)U(Y_f) \qquad [2]$$

For the stochastic term on the right-hand side we apply a third-order Taylor expansion around the expected value Y_r, one order up from Pratt's original contribution (Pratt, 1964), to

$$\int_0^T U(Y_r + \varepsilon)\,e^{-\delta t}dt = \frac{1}{\delta}\left(1 - e^{-\delta T}\right) \qquad [3]$$
$$\left[U(Y_r) + \frac{1}{2}U''(Y_r)\,\sigma_p^2 + \frac{1}{6}U'''(Y_r)\,\kappa_p^3\right]$$

where σ_p^2 is the second moment and κ_p^3 is the third moment of ε around the expected value of zero. We will denote the second moment as risk and the third as skewness (in the life cycle consumption-saving literature it is known as *prudence*). Equating [2] and [3] and rewriting a little, after applying a first-order Taylor expansion around Y_r for [2], we get

$$\frac{Y_r - Y_f}{Y_r} = -\frac{1}{2}\frac{\sigma_p^2}{Y_r^2}\frac{U''}{U'}Y_r - \frac{1}{6}\frac{\kappa_p^3}{Y_r^3}Y_r\frac{U''}{U'}Y_r = \frac{1}{2}\frac{\sigma_p^2}{Y_r^2}V_r - \frac{1}{6}\frac{\kappa_p^3}{Y_r^3}V_sV_r \qquad [4]$$

where V_r is Arrow-Pratt's relative risk aversion and V_s is the similar definition for relative skewness affection (we call it affection, because individuals like skewness; see Hartog and Vijverberg, 2002). With V_r and V_s positive by definition, we note from [4] that individuals only enter an education if the income risk in it is matched by a positive premium, while they allow an earnings drop for skewness.

Equation [4] specifies the compensation for income uncertainty relative to a fixed income. Of course there will also be compensation for postponing earnings while in school. By moving from earnings maximization to utility maximization, this compensation will depend on the nature of the utility function. If we assume a utility function with CRRA, i.e.

$$U(Y) = \frac{1}{1-\rho}Y^{1-\rho} \qquad [5]$$

compensation for every year in school can be derived as $\delta/(1-\rho)$. If we now generalise the situation to many different levels or types of education, differing in length s, and still assume CRRA, we can write the earnings function containing compensation for earnings postponement and for earnings uncertainty as

$$E(\ln Y_s) = \ln Y_0 + \frac{\delta}{1-\rho}s + \frac{1}{2}\rho\frac{m_{2s}}{\mu_s^2} - \frac{1}{6}\rho(\rho+1)\frac{m_{3s}}{\mu_s^3} \qquad [6]$$

with μ_s expected earnings in the education taking s years of schooling and

$$\frac{m_{2s}}{\mu_s^2} = \frac{E\left[(Y_s-\mu_s)^2\right]}{\mu_s^2} = E\left[\left(\frac{Y_s-\mu_s}{\mu_s}\right)^2\right] \qquad [7]$$

$$\frac{m_{3s}}{\mu_s^3} = \frac{E\left[(Y_s-\mu_s)^3\right]}{\mu_s^3} = E\left[\left(\frac{Y_s-\mu_s}{\mu_s}\right)^3\right] \qquad [8]$$

If we do not assume CRRA, the parameters of the earnings function are not constant but will depend on income levels. But clearly, the Mincer earnings equation augmented with relative risk and relative skewness, as a linearization, is a good starting point for empirical work to investigate whether wages indeed respond to uncertainty. Note also that under earnings maximization ($\rho = 0$), [6] reduces to the standard Mincer equation.

3. Empirical framework

As in McGoldrick (1995), we first decompose earnings according to the source of variation, i.e. a systematic and an unsystematic component. Systematic fluctuations in earnings are caused by supply variables (such as work experience), which are usually anticipated by individuals, and therefore, have nothing to do with risk. However, unsystematic variations in earnings catch variations which are unknown by individuals when they have to make their educational choice. They indeed reflect the risk to individuals: their as yet unknown abilities, suitability for the education chosen, and hence the relative position in the earnings distribution at which they will end up. They also reflect demand factors (e.g. business cycle, shocks in output demand and the consequent movements in the employment rates) and they are expected to generate compensating wage differentials, from supply behavior in a competitive market.

We first estimate the following log-earnings equation

$$\ln Y_{ij} = X_{ij}\beta + u_{ij}, \qquad [9]$$

where Y_{ij} are the observed earnings of individual i with the type of education j, X_{ij} are the observable determinants of Y_{ij} expected to generate systematic variations in earnings, and u_{ij} is a disturbance term. The variables included in X_{ij} are years of schooling, a squared polynomial on age, a dummy for gender, and a set of regional dummies. We use age instead of potential years of experience for the following reasons; firstly, age is exogenous, and; secondly, experience is commonly rescaled age anyway (as actual experience is not observed). Additionally, equation [9] can be augmented as follows

$$\ln Y_{ij} = X_{ij}\beta + \sum_j \gamma_j E_{ij} + u_{ij}, \qquad [10]$$

where E_{ij} are dummies for each education type, i.e. E_{ij} takes the value one if individual i possesses the education type j and zero otherwise. The education fixed-effects, γ_j, control for the omission of variables and specific attractions of levels or types of education that go unmeasured and that might bias our measures of earnings risk (R) and skewness (K). From equation [9] or [10] R and K are estimated using three different specifications.

Model 1

As a start, we proxy earnings risk (R) and skewness (K) by the second and third moment of the unsystematic earnings distribution as follows

$$R_j = E_j \left\{\widehat{\eta}_{ij} - E_j\left(\widehat{\eta}_{ij}\right)\right\}^2 \qquad [11]$$

$$K_j = E_j \left\{\widehat{\eta}_{ij} - E_j\left(\widehat{\eta}_{ij}\right)\right\}^3 \qquad [12]$$

where $\widehat{\eta}_{ij} = \exp\left(\widehat{u}_{ij}\right)$ and the exponential transformation on the estimated residuals $\widehat{u}_{ij}$ is applied in order to transfer unsystematic earnings back to the money metric. The measures R and K expressed in [11] and [12] are the original measures as defined in McGoldrick (1995).

Model 2

Hartog and Vijverberg (2002) derive different measures of R and K, which also acknowledge the common deviation of earnings distributions from normality; they apply a correction that would hold exactly under log-normality (which does not hold either, but the correction reduces the bias). These measures are directly derived from expressions [7] and [8] and are defined as follows

$$R_j = \frac{1}{N_j} \sum_{i=1}^{N_j} \left(\frac{Y_{ij} - \widehat{Y}_{ij}}{\widehat{Y}_{ij}} \right)^2, \qquad [13]$$

$$K_j = \frac{1}{N_j}\sum_{i=1}^{N_j}\left(\frac{Y_{ij}-\widehat{Y}_{ij}}{\widehat{Y}_{ij}}\right)^3 \qquad [14]$$

where $\widehat{Y}_{ij} = \exp\left(X_i\widehat{\beta}+\widehat{\sigma}_j^2/2\right)$ and $\widehat{\sigma}_j^2$ is the estimated variance of the estimated residuals, $\widehat{u}_{ij}$, for each education group j in equation [9] or [10]. In contrast with R and K defined in equation [11]-[12], the measures defined in equation [13]-[14] are the relative variance and skewness of the unsystematic earnings distribution.

Model 3

Finally, also following Hartog and Vijverberg (2002) we use alternative measures of R and K to test for the robustness of our conclusions:

$$R_j = P_{75} - P_{25}, \qquad [15]$$

$$K_j = \frac{(P_{75}-P_{50})}{(P_{50}-P_{25})} \qquad [16]$$

where P_{25}, P_{50} and P_{75} are the 25^{th}, 50^{th} and 75^{th} percentiles of the estimated residuals from equation [9] or [10] within education j, respectively. Alternatively, since [15] and [16] are used in order to construct measures fully robust to the presence of outliers and top coding, in addition to the OLS residuals we also use the residuals from a median regression in the first stage.

Once R and K are estimated in the first round by either equations [11]-[12], [13]-[14] or [15]-[16], they are plugged in a fully specified earnings equation as follows

$$\ln Y_{ij} = Z_i\delta + \alpha R_j + \lambda K_j + \varepsilon_{ij}, \qquad [17]$$

where Z_i includes the variables used in X_i plus other determinants of earnings.

The existence of a risk compensation requires $\alpha > 0$, whereas the willingness to pay for positive skewness, the so called *skewness affection,* requires $\lambda < 0$. One might expect the education fixed-effects γ_j in expression [10] to be known by individuals, and hence, we calculated risk and skewness around the educational mean. However, we cannot include the education fixed effects in the second round, as we have already fixed R and K for a given education. The interpretation of α in equation [17] is the extra relative wage that an individual requires for an additional unit of risk (as specified in the three models). Similarly, λ is the wage share that an individual is willing to pay for an additional unit of positive relative skewness.

We should note that, essentially, we only test whether there is any compensation for earnings uncertainty associated with schooling choices. We have presented a simple model for individuals' reactions to this uncertainty and we predict that the market wage will reflect this, imposed by supply behavior. Only under the strictest conditions will this identify a structural parameter. If all individuals indeed get their information on risk and skewness from the residual earnings distributions, as we have assumed, and have identical risk attitudes, the estimated coefficients identify the individual's reservation prices. If individuals differ in risk attitudes, we can at best identify the reservation price of the marginal worker. If individuals act on other information, and have better information than we as researchers have on their abilities and the associated risk and skewness of earnings, then the estimated coefficients may be biased; the direction of that bias is not obvious however (see Hartog and Jacobs, 2005). Empirical evidence on individuals' actual perceptions of future earnings variability is scant. Dominitz and Manski (1996) is one of the very few studies with direct observations; they indicate that earnings variance as expected by students is certainly not less than the actual variance observed for individuals who have already completed the relevant education.

4. Data description

To carry out the empirical analysis we use the Spanish *Encuesta de Estructura Salarial* (Salary Structure Survey) of 1995. This is a nationwide survey across workers employed in the manufacturing industry and services (agriculture, forestry and fishing are not included), distinguishing several sources of earnings (gross, net, etc.). The earnings used in this study are net hourly earnings, as this is what workers respond to. These are calculated by dividing the annual net earnings by the total amount of annual hours worked. In order to avoid extra sources of variability that can distort the calculation of R and K, from the full sample we have selected just full-time workers with open-ended contracts, thus eliminating part-time and fixed-term contract workers. The number of observations in the survey equals 152,923, of which 109,325 observations refer to full-time and open-ended contract workers. From the former group 87,269 are men and 22,056 are women.

One limitation of the survey is that it does not allow controlling for selectivity bias in the female participation decision. However, it provides an extensive classification of the worker's education with 66 education cells. This feature makes this survey the most suitable for our purposes. This is a clear advantage over other Spanish surveys where the educational classification is just limited to the level of education (8-9 cells), thus ignoring the type of education, which is critical when analyzing risk compensation in wages.

In order to estimate R and K consistently we need a minimum number of observations in each education cell. Following Hartog and Vijverberg (2002) we fix this number at 6 observations[4]. This restriction leaves53 effective education cells for the full sample (109,298 observations), 52 for men (87,241 observations) and 43 for women (22,027 observations). In table A1 (Appendix) we show the number of individuals in each education cell for the full sample and by gender.

5. Empirical results

5.1 Estimates of R and K

In this section we present the empirical results derived from the OLS estimates of wage equation [17]. The endogenous variable is net hourly earnings. We run regressions for the full sample, and also separate regressions for men and women. Since our data only provides information from workers (non-participants in the labor market are not included in the sample), we cannot apply the standard Heckman (1976) selectivity bias correction procedure for the female wage regressions[5].

As we mention in Section 4 our strategy is to use a two-step estimation method. In the first round we estimate equation [9] or [10], estimate R and K and plug these variables in an earnings equation to evaluate risk compensation and the skewness *penalty* in wages. For the separate estimates for men and women, this two-step process is done separately. In the case of equation [9] the exogenous variables are years of schooling, a squared polynomial on age, a dummy for gender and a set of regional dummies. Gender is omitted in the separate estimates for men and women. In equation [10] years of schooling is omitted since in this

[4]Including education cells with less than 6 observations produces no changes in our estimates.

[5]In a related work using the Encuesta de Presupuestos Familiares 1990/91 (see Díaz-Serrano, 2001) the use of the Heckman correction method results in negligible changes compared to the specification that does not control for selectivity bias.

specification we already include a set of dummies for each education cell. OLS estimates of equation [9] and [10] are not reported but all the variables display expected effects, positive for years of schooling, positive and decreasing for age and negative for gender (female).

Table 1 shows summary statistics of the estimates R and K. The labels "without FE" and "with FE" refer to R and K estimated with the residuals from equations [9] and [10], respectively, while models 1, 2 and 3 refer to the estimates of R and K coming from equations [11]-[12], [13]-[14], and [15]-[16], respectively. Recall that the difference between equations [9] and [10] is that the latter includes education fixed-effects. These different methods for estimating R and K give rise to some systematic differences. When we use equation [9] R and K show higher average values and dispersion than with equation [10]. Probably, this result is due to the fact that omitting the education fixed-effects leads to some upward bias in R and K since these fixed-effects control for the potential omission of variables in the first round. Analogously, estimates of R and K coming from equation [11]-[12] tend to be systematically higher than estimates coming from equation [13]-[14]. We also observe that estimates of R and K tend to be higher for men than for women.

In the second stage estimation, we cannot include these education fixed-effects. However, we can test whether R and K just pick up fixed-effects, or possibly represent something else than earnings variability, by regressing the education fixed-effects, γ, on R and K: $\gamma_j = \beta_0 + \beta_1 R_j + \beta_2 K_j + \upsilon_j$. If R and K just represent fixed effects they should predict the estimated fixed effects. Results reported in Table 2 confirm the absence of this type of bias in R and K.

Table 1
Summary statistics for R and K

		Full					Men					Women				
		Mean	St. Dev.	5th	50th	95th	Mean	St. Dev.	5th	50th	95th	Mean	St. Dev.	5th	50th	95th
Model 1	With FE															
	R	0.157	0.041	0.116	0.138	0.249	0.179	0.086	0.129	0.146	0.348	0.170	0.039	0.115	0.162	0.240
	K	0.167	0.317	0.062	0.096	0.283	0.506	1.481	0.067	0.118	3.169	0.136	0.068	0.044	0.151	0.265
	Without FE															
	R	0.194	0.095	0.138	0.165	0.489	0.184	0.103	0.118	0.151	0.435	0.161	0.042	0.109	0.156	0.203
	K	0.631	1.706	0.079	0.135	5.059	0.592	1.778	0.071	0.122	4.232	0.437	0.601	0.039	0.111	1.494
Model 2	With FE															
	R	0.136	0.032	0.105	0.121	0.205	0.155	0.069	0.116	0.129	0.301	0.143	0.027	0.103	0.142	0.198
	K	0.133	0.259	0.053	0.076	0.222	0.387	1.109	0.057	0.098	2.543	0.098	0.051	0.037	0.106	0.209
	Without FE															
	R	0.142	0.046	0.106	0.125	0.214	0.165	0.086	0.113	0.133	0.364	0.144	0.040	0.101	0.132	0.176
	K	0.132	0.219	0.027	0.058	0.594	0.466	1.355	0.035	0.103	3.488	0.341	0.446	0.011	0.088	1.121
Model 3	OLS regression															
	R	0.115	0.031	0.066	0.122	0.140	0.124	0.038	0.061	0.118	0.161	0.112	0.031	0.066	0.109	0.140
	K	0.794	0.372	0.410	0.802	1.303	0.632	0.256	0.230	0.482	1.190	0.776	0.382	0.337	0.802	1.303
	Median regression															
	R	0.116	0.032	0.071	0.120	0.143	0.126	0.038	0.061	0.122	0.163	0.113	0.031	0.071	0.115	0.143
	K	0.779	0.376	0.359	0.777	1.332	0.618	0.244	0.231	0.482	1.137	0.754	0.380	0.331	0.776	1.332

Notes: Model 1: R and K estimated with equation (11)-(12); model 2: R and K estimated with equation (13)-(14); model 3: R and K estimated with equation (15)-(16); "Without FE": R and K estimated with equation (9); "With FE": R and K estimated with equation (10); "OLS Regression": R and K estimated using the residuals from OLS regression in the first stage; "Median Regression": R and K estimated using the residuals from median regression in the first stage.

TABLE 2
OLS estimates of the equation $\gamma_j = \beta_0 + \beta_1 R_j + \beta_2 K_j + \upsilon_j$.

Full sample	Men		Women			
	Model 1	Model 2	Model 1	Model 2	Model 1	Model 2
Constant	0,282	0,22	0,221	0,245	0,339	0,304
	0,059	*0,096*	*0,079*	*0,098*	*0,059*	*0,068*
R	0,291	0,629	0,471	0,418	-0,1	0,368
	0,265	*0,699*	*0,362*	*0,697*	*0,333*	*0,613*
K	$6{,}7\cdot10^{-6}$	0,046	$1{,}0\cdot10^{-5}$	0,058	$-2{,}7\cdot10^{-5}$	-0,299
	$1{,}1\cdot10^{-5}$	*0,092*	$1{,}3\cdot10^{-5}$	*0,073*	$3{,}0\cdot10^{-5}$	*0,214*
R^2	0.003	0.014	0.036	0.020	0.019	0.004

Note: Endogenous variable is the estimated fixed-effects in equation (10).

5.2 *OLS estimates of the risk premium and skewness affection reduction*

We present our key results in Tables 3 to 5, for schooling, R and K. We report the OLS estimates of equation [17]. In these equations the covariates are R, K, years of schooling, a squared polynomial in age and tenure, hours worked, and a set of dummies for gender, industry, public/private sector and unionization. For the sake of brevity we just report the results concerning years of schooling, R and K. We experiment with three different basic specifications: i) excluding R and K (not reported); ii) just including R; and iii) including R and K. The first specification is used to assess a possible omitted-variable bias from ignoring risk and skewness in the standard Mincer rate-of-return estimates, whereas the second specification is used to assess the sensitivity of the coefficient of R to the omission (inclusion) of K. In general we can draw the conclusion that earnings compensate the risk-averse worker: a positive effect for risk and a negative effect for skewness by education groups, statistically highly significant in all specifications.

Table 3
OLS estimates of equation (17). Full sample (size=109,298)

	Model 1								Model 2								Model 3			
	With FE				Without FE				With FE				Without FE				OLS residuals			
	Coeff.	s.e.	Coeff.	s.e.	Coeff.	s.e.	Coeff.	s.e.	Coeff.	s.e.	Coeff.	s.e.	Coeff.	s.e.	Coeff.	s.e.	Coeff.	s.e.	Coeff.	s.e.
Schooling	0.050	$4\cdot10^{-4}$	0.052	$4\cdot10^{-4}$	0.056	$4\cdot10^{-4}$	0.056	$4\cdot10^{-4}$	0.053	$4\cdot10^{-4}$	0.053	$4\cdot10^{-4}$	0.056	$4\cdot10^{-4}$	0.056	$4\cdot10^{-4}$	0.057	$3\cdot10^{-4}$	0.057	$3\cdot10^{-4}$
		0.002		*0.002*		*0.002*		*0.002*		*0.002*		*0.002*		*0.002*		*0.002*		*0.001*		*0.001*
R	0.629	0.015	1.139	0.018	0.508	0.019	0.584	0.027	1.199	0.017	1.425	0.029	0.637	0.024	0.790	0.054	0.222	0.041	0.307	0.041
	0.122	*0.045*	*0.222*	*0.069*	*0.080*	*0.059*	*0.092*	*0.107*	*0.170*	*0.048*	*0.202*	*0.084*	*0.087*	*0.073*	*0.108*	*0.153*	*0.025*	*0.139*	*0.035*	*0.152*
			-0.034	0.002			-0.013	0.003			-0.060	0.002			-0.024	0.003			-0.020	0.003
			-0.021	*0.014*			*-0.002*	*0.017*			*-0.008*	*0.006*			*-0.003*	*0.010*			*-0.016*	*0.008*
R^2	0.520		0.523		0.485		0.513		0.520		0.520		0.485		0.513		0.512		0.509	

Notes: Model 1: R and K estimated with equation (11)-(12); model 2: R and K estimated with equation (13)-(14); model 3: R and K estimated with equation (15)-(16); "Without FE": R and K estimated with equation (9); "With FE": R and K estimated with equation (10); "OLS Regression": R and K estimated using the residuals from OLS regression in the first stage; "Median Regression": R and K estimated using the residuals from median regression in the first stage.
Elasticity: Italic font in column labeled as Coeff.
Corrected standard errors are in Italic font in the column labeled as s.e.

Table 4
OLS estimates of equation (17). Men (size=87,241)

	Model 1								Model 2								Model 3			
	With FE				Without FE				With FE				Without FE				OLS residuals			
	Coeff.	s.e.	Coeff.	s.e.	Coeff.	s.e.	Coeff.	s.e.	Coeff.	s.e.	Coeff.	s.e.	Coeff.	s.e.	Coeff.	s.e.	Coeff.	s.e.	Coeff.	s.e.
Schooling	0.049	$4\cdot10^{-4}$	0.050	$4\cdot10^{-4}$	0.051	$4\cdot10^{-4}$	0.051	$4\cdot10^{-4}$	0.049	$4\cdot10^{-4}$	0.050	$4\cdot10^{-4}$	0.051	$4\cdot10^{-4}$	0.051	$4\cdot10^{-4}$	0.050	$4\cdot10^{-4}$	0.051	$4\cdot10^{-4}$
		0.002		*0.002*		*0.002*		*0.002*		*0.002*		*0.002*		*0.002*		*0.002*		*0.001*		*0.001*
R	0.602	0.015	1.077	0.030	0.510	0.020	0.634	0.045	0.749	0.018	1.170	0.033	0.650	0.025	0.864	0.061	0.202	0.041	0.269	0.047
	0.111	*0.043*	*0.198*	*0.066*	*0.091*	*0.056*	*0.114*	*0.103*	*0.123*	*0.046*	*0.193*	*0.082*	*0.101*	*0.069*	*0.134*	*0.145*	*0.028*	*0.136*	*0.033*	*0.151*
K			-0.031	0.001			-0.007	4·10-4			-0.032	0.002			-0.013	0.003			-0.016	0.003
			-0.018	*0.006*			*-0.004*	*0.002*			*-0.015*	*0.006*			*-0.005*	*0.009*			*-0.010*	*0.008*
R^2	0.489		0.492		0.483		0.485		0.490		0.492		0.485		0.485		0.458		0.457	

Notes: Model 1: *R* and *K* estimated with equation (11)-(12); model 2: *R* and *K* estimated with equation (13)-(14); model 3: *R* and *K* estimated with equation (15)-(16); "Without FE": *R* and *K* estimated with equation (9); "With FE": *R* and *K* estimated with equation (10); "OLS Regression": *R* and *K* estimated using the residuals from OLS regression in the first stage; "Median Regression": *R* and *K* estimated using the residuals from median regression in the first stage.
Elasticity: Italic font in column labeled as Coeff.
Corrected standard errors are in Italic font in the column labeled as s.e.

Table 5
OLS estimates of equation (17).Women (size=22,027)

	Model 1								Model 2								Model 3			
	With FE				Without FE				With FE				Without FE				OLS residuals			
	Coeff.	s.e.	Coeff.	s.e.	Coeff.	s.e.	Coeff.	s.e.	Coeff.	s.e.	Coeff.	s.e.	Coeff.	s.e.	Coeff.	s.e.	Coeff.	s.e.	Coeff.	s.e.
Schooling	0.059	0.001	0.057	0.001	0.058	0.001	0.058	0.001	0.058	0.001	0.056	0.001	0.057	0.001	0.058	0.001	0.054	0.001	0.053	0.001
		0.002		*0.002*		*0.002*		*0.002*		*0.002*		*0.002*		*0.002*		*0.002*		*0.002*		*0.002*
R	0.286	0.035	0.832	0.041	0.421	0.045	0.718	0.062	0.610	0.041	1.109	0.072	0.733	0.056	1.119	0.131	0.408	0.096	0.393	0.101
	0.046	*0.069*	*0.134*	*0.094*	*0.072*	*0.089*	*0.122*	*0.125*	*0.062*	*0.076*	*0.160*	*0.135*	*0.105*	*0.111*	*0.160*	*0.240*	*0.047*	*0.193*	*0.045*	*0.218*
K			-0.102	0.006			-0.228	0.001			-0.142	0.004			-0.284	0.007			-0.025	0.007
			-0.045	*0.017*			*-0.031*	*0.079*			*-0.048*	*0.080*			*-0.028*	*0.014*			*-0.019*	*0.012*
R^2	0.489		0.499		0.490		0.490		0.490		0.500		0.490		0.491		0.491		0.492	

Notes: Model 1: *R* and *K* estimated with equation (11)-(12); model 2: *R* and *K* estimated with equation (13)-(14); model 3: *R* and *K* estimated with equation (15)-(16); "Without FE": *R* and *K* estimated with equation (9); "With FE": *R* and *K* estimated with equation (10); "OLS Regression": *R* and *K* estimated using the residuals from OLS regression in the first stage; "Median Regression": *R* and *K* estimated using the residuals from median regression in the first stage.
Elasticity: Italic font in column labeled as Coeff.
Corrected standard errors are in Italic font in the column labeled as s.e.

We do not observe omitted-variable bias in the returns to schooling due to the neglect of uncertainty. In all specifications (with and without risk and skewness) the returns to schooling take values between 5 and 5.8%. In models 1 and 2 the estimated coefficient for risk is sensitive to the inclusion of skewness, whereas it is not so in model 3. One possibility is that this sensitivity in models 1 and 2 may be due to multi-collinearity patterns. In table 6 we show the correlation coefficient between R and K across alternative measures and samples. For model 3 correlation is generally modest, between 0.23 and 0.29 for the full sample and women, and between -0.41 and -0.35 for men. However, in models 1 and 2 the correlations exhibit quite different patterns: from 0.36 for women, when R and K are estimated without education fixed-effects in the first round, to 0.75 for men when R and K are estimated with education fixed-effects in the first round. But we cannot find any systematic pattern in the estimation results and the correlation between R and K; estimation with or without education fixed-effects in the first round can provide a higher or lower coefficients depending on the sample. In some cases correlation patterns are modest but even in the most extreme case, 0.75, we cannot consider this value as critical for our estimates. Indeed, we observe that the highest sensitivity of the coefficients of R to the inclusion of K are not associated with the highest correlations. For instance, take the estimates for the full sample in model 1 (Table 3). In this model the risk coefficient, with risk estimated without education fixed-effects, raises from 0.62 to 1.1 once skewness is included, and with a correlation of 0.42 between R and K. When risk is estimated with education fixed effects, this coefficient increases from 0.50 to 0.58 when skewness is included and with a correlation coefficient of 0.55 between R and K. This result indicates that a higher correlation does not necessarily lead to a greater sensitivity of the risk coefficient once skewness is included. Analogous conclusions can be drawn from the estimates coming from the separate samples of men and women.

TABLE 6
Pearson correlations between R and K

	Full sample	Men	Women
Model 1			
With FE	0.557	0.718	0.749
Without FE	0.424	0.724	0.366
Model 2			
With FE	0.588	0.755	0.733
Without FE	0.648	0.745	0.406
Model 3			
OLS regression	0.294	-0.408	0.283
Median regression	0.235	-0.349	0.231

Note: See table 3.

To assess economic significance, we converted the estimates into elasticities (italic font in the column labeled as Coeff. in table 3 to 5). Elasticities are generally low, and vary across alternative samples and models. We focus now on the estimated elasticities for men and women in models 1 and 2 with full specification (including R and K). In general, for women the wage elasticity of risk is smaller that for men, whereas the reverse pattern holds for the wage elasticity of skewness. For men the wage elasticity of risk is mostly in the interval 0.09 to 0.22, whereas for women this interval ranges from 0.12 to 0.16. The wage elasticities of skewness are generally smaller than the wage elasticities of risk, from –0.004 to –0.018 for men, and from –0.031 to –0.048 for women. In the case of model[6] 3 the pattern of the wage elasticity of risk reverses in comparison with models 1 and 2, and we observe a higher effect for women than for men, 0.045 vs. 0.033, whereas we observe the same pattern for the wage elasticity of skewness, -0.019 vs. –0.01.

5.3 Assesing robustness: generated regressors and clustering correction

The estimation of our model hinges on the inclusion of unobservable but estimable variables (R and K). As usual in this sort of models, we use the two-step econometric procedure consisting of replacing the unobserved R and K by their predicted values from an auxiliary re-

[6] For the sake of brevity, for model 3 we do not report the results concerning R and K computed with the residuals coming from a median regression. These results are practically identical to the ones provided by OLS residuals.

gression model. Both R and K are estimated by education groups. The critical issue in this model is twofold. Firstly, while the estimates of the parameters in the second-step are consistent, the consequent estimated standard errors are generally incorrect. This is due to the fact that the two-stage method does not take into account that the unobservable regressors obtained in the first round might be estimated with sampling error. And secondly, the fact that R and K are constant within each education cell gives rise to the well-known Moulton-type problem of clustered observations within cells. In the first case, Murphy and Topel (1985) show that under some general conditions the limiting distribution of this sampling error may be used to consistently estimate the variances of the second step parameter estimates. In the second case, Moulton (1986) proposes a clustering-robust estimation procedure. Since our estimates are affected by both issues, we propose a method to estimate the standard errors of the estimated parameters consisting by mixing both Murphy-Topel's and Moulton's corrections.

Now go back to model [17] but now consider residual ε_{ij} as the sum of a group specific component (α_j) and an individual specific component (η_{ij})

$$\varepsilon_{ij} = \alpha_j + \eta_{ij}, \qquad [18]$$

with j ranging from 1 to J and i from 1 to N. Moulton (1986) shows that the true covariance matrix of the OLS estimator of β is

$$V = \sigma^2 \left(M'M\right)^{-1} \left[I + \rho \left(H - I\right)\right], \qquad [19]$$

where $\rho = \sigma_\alpha^2 / \left(\sigma_\alpha^2 + \sigma_\eta^2\right)$, $M = [Z, R, K]$ is a matrix containing the regressors in model [17] and $H = M'DD'M \left(M'M\right)^{-1}$, where D is a NxJ matrix of 0-1 indicators for membership in any of the G groups. Our proposition is to replace [19] the conventional OLS covariance matrix estimator $\sigma^2 \left(M'M\right)^{-1}$ by the alternative covariance matrix estimator proposed in Murphy and Topel (1985) to avoid the problems caused by the fact that R and K in model [17] are generated regressors from a first-stage regression. Thus, the consistent covariance matrix would read now as:

$$V = \textstyle\sum_M \left[I + \rho \left(H - I\right)\right], \qquad [20]$$

where

$$\begin{aligned} \textstyle\sum_M \;=\; & \sigma_M^2 Q_0^{-1} + Q_0^{-1} \{ Q_1 + R_1^{-1} (\beta) Q_1' - \qquad [21] \\ & - Q_1 R_1^{-1} (\beta) Q_2' - Q_2 R_1^{-1} (\beta) Q_1' \} Q_0^{-1\prime} \end{aligned}$$

and $Q_0 = N^{-1}M'M$; $Q_1 = N^{-1}M'F^*$; $Q_2 = N^{-1}\sum_{i=1}^{N} M_i'\widehat{\varepsilon}_i l'(X_i;\beta)$ where $\widehat{\varepsilon}$ denotes the estimated residuals of the second-stage regression, i.e. model [17], $l'(\bullet)$ is the column vector of first derivatives of the log-likelihood with respect to β in the first-stage regression, i.e. model [9] or [10]; $F^* = \hat{\beta}X$ and[7]

$$R_1(\beta) = -E\left[N^{-1}\left\{\frac{\partial^2 l(X;\beta)}{\partial\beta\partial\beta'}\right\}\right], \qquad [22]$$

is the Fisher's information matrix from the first-step regression. The use of equation [22] is motivated by the fact that the second-stage model (equation [17]) and the first-stage model (equation[9]) are estimated using the same and contemporaneous data. Equation [22] accounts for this dependency between the random components[8].

The corrected standard errors of equation [20] are reported in italic font in the column labeled as s.e. in tables 3, 4 and 5. Although the correction in the standard errors is quite important, in almost all cases the parameters associated not only to R and K but also to the remaining explanatory variables (not reported) are still significant at 5 percent or better. Only the parameters associated to skewness in model 1 with fixed-effects for the full sample and to skewness in model 2 without fixed effects for men have turned out to be statistically not significant after applying the correction of the standard errors expressed in equation [20]. It is noteworthy that the most important effect in the correction of the standard errors comes from the clustering correction. The effect of the correction on R and K coming from equation [22] is almost negligible, whereas this correction is more important, but still fairly modest, for other explanatory variables (not reported).

6. Summary and concluding remarks

In this study we report the existence of compensating wage differentials for schooling as a risky investment in the Spanish labor market. The significance of such compensation across alternative samples and models reveals that the finding is robust. Our results are consistent with previous evidence for the US and Denmark. However, direct comparisons of our results are only feasible for Denmark (Díaz-Serrano,

[7] Ideally, we could specify F^* to collect the nonlinear nature of R and K. However, as we will see the effect of including such a refinement would be negligible.
[8] See Murphy and Topel (1985) for more details.

Hartog and Nielsen, 2003), since this is the unique previous study where the risk and skewness measures are just based on education cells. From these results we conclude that the risk-return trade-off in educational choices is well established. The estimation results are consistent with the preferences of risk averse agents with declining absolute risk aversion. However, our results regarding women should be interpreted with some caution, since the nature of our data set did not allow us to control for selectivity bias. Therefore, although the results for women are plausible, we do not dare to conclude if the size of the compensation/penalty is smaller or bigger than for men.

As the evidence in other studies shows, our results concerning the negative skewness effect in wages mirror real preferences. Garrett and Sobel (1999) derive a utility function for participants in US state lotteries from data on probabilities and prize money, and conclude, in their title: 'Gamblers favor skewness not risk'. Similarly, Golec and Tamerkin (1998) demonstrate that 'Bettors love skewness, not risk, at the horse track'. It seems then, that these results generalize from lotteries and horse tracks to labor markets and schooling choices. Of course, these are very different choices but they share a common feature, i.e. all of them involve a choice with a pecuniary cost with an uncertain outcome. One may of course speculate that other explanations also fit our results. However, we have not seen any such alternative offered in the literature. An obvious and simple approach might be to assume a normal distribution of innate, pre-school ability, and individuals selecting themselves into higher levels of schooling based on their ability (and other considerations of course). Successive levels of schooling would then be successive slices of the innate ability distribution. It is easy to show that in such slices one cannot expect the result we found: a mean that is positively associated with the variance and negatively with skewness. Hence, an alternative explanation is by no means obvious.

This evidence for Spain sets an interesting agenda for empirical work. One may compare our cross-section estimates of earnings risk with estimates based on panel data (Díaz-Serrano, Hartog and Nielsen 2003). Developing and estimating a structural model (Hartog and Vijverberg, 2002) would be quite interesting, as shown by Abowd and Ashenfelter (1981) with respect to compensation for unemployment risk. And of course, allowing for self-selection, based on direct measurement of differences in individual risk attitudes, would be an exciting topic for further research. Unfortunately, data allowing such a refinement are not available. We believe to have shown that differences in the probability of success within an education deserve more attention than they have so far obtained. We recognize that as in Díaz-Serrano, Hartog and Nielsen (2003), measures capturing the dynamic nature of risk would provide a more suitable framework. However, such long and rich panel data sets are rarely available for most countries.

Unemployment risk and compensation in wages is another interesting issue. However, one may suspect the compensation for earnings variability to be much more important, simply because earnings variability is much larger. For example, for the US Murphy and Topel (1987:109) report a coefficient of variation of 0.24 for the hourly wage rate and 0.067 for annual hours worked. Back of the envelope calculations also suggest that earnings variabilitly is much larger and from that perspective the first effect to be considered. Suppose for example that every individual faces an annual unemployment risk of 10% and, when unemployed, receives 70% of his earnings, and let us evaluate unemployment only in terms of lost income. Then, relative earnings risk m_2/μ^2 equals 0.008. Then, with a risk aversion coefficient[9] of V_r of about 0.5, equation [4] predicts an earnings premium of 0.2%. By contrast, relative earnings risk is in the order of 0.6, according to the studies we have made so far for various countries (Hartog, 2005), which would require a wage premium of 15%. Turning again to the US, for which most information is available, Abowd and Ashenfelter (1981) estimate wage compensation for anticipated unemployment risk in the context of a structural model, and indeed estimate a high coefficient of hours risk aversion (the counterpart of the Arrow-Pratt measure of income risk aversion), at values around 14. But when applied to actually experienced unemployment, the compensating wage differential is in the order of 4%. Murphy and Topel (1987) find that a one standard deviation increase in the variability of weeks worked would generate compensation in average annual earnings of about 0.5%. Naturally, a model including both wage and unemployment risk is preferable to a model considering only wage risk. Thus, we can add that to the list of further work, but in our view not at top priority.

[9] See Hartog and Vijverberg (2002) for estimates and references to the related literature.

Appendix A1: The educational groups

Table A1.1
Summary statistics for net hourly earnings by education cells

Full sample					Men			Women		
Educational Groups (Spanish Classification)	Equivalence with ISCED[(a)]	Mean	St.D.	N	Mean	St.D.	N	Mean	St.D.	N
Sin estudios o con estudios primarios incompletos	*Pre-primary education*									
Analfabetos	Illiterate	6.52	2.89	697	6.65	2.67	665	5.60	3.29	92
Menos de 5 años de primaria	Less that 5 years	6.64	2.40	185	6.86	2.41	165	4.83	1.20	20
Preescolar	Preschool	5.43	2.19	15	6.22	2.17	9	3.65	0.72	6
Estudios primarios incompletos	Incomplete primary	6.82	2.83	1,994	7.12	2.78	1,727	4.92	2.42	267
Educación primaria completa	*Primary education or first stage of basic education*									
Sin especificar	Not specified	7.36	33.00	2,634	7.72	35.81	2,234	5.30	2.07	400
Estudios primarios completos	Complete primary	7.00	2.76	32,167	7.28	2.77	27,284	5.42	2.07	4,883
Enseñanza General Básica (EGB) - 1ª etapa (5 años)	General education (5 years)	6.94	3.27	1,377	7.34	3.32	1,145	4.95	2.06	232
Educación General Básica Completa o equivalente en Educación Secundaria	*Lower secondary or second stage of basic education*									
Sin especificar	Not specified	6.15	2.50	1,573	6.46	2.57	1,258	4.89	1.67	315
Bachiller elemental	Elementary high-school diploma	9.12	4.14	4,951	9.57	4.32	3,915	7.42	2.77	1,036
Graduado escolar (EGB completa)	General education diploma (8 years)	6.25	2.72	22,224	6.67	2.73	16,902	4.88	2.16	5,322
Certificado de escolaridad	General education without graduation (8 years)	7.47	3.41	1,311	8.00	3.44	1,052	5.33	2.30	259
Educación secundaria obligatoria	Compulsory secondary education	7.76	3.93	55	8.13	4.24	42	6.56	2.40	13
Aprendizaje de tareas	Apprenticeship	9.44	3.36	55	10.14	3.80	37	7.99	1.45	18
Bachillerato	*Upper secondary education (High-School)*									
Sin especificar	Not specified	9.55	3.37	1,072	9.61	3.81	624	9.46	2.65	448
Bachiller superior	High-school diploma (previous to the 1970 educational reform)	10.21	4.60	6,034	10.83	4.75	4,688	8.06	3.19	1,346
BUP con/sin COU	High-school diploma (1970 educational reform)	8.72	4.31	6,589	9.53	4.62	4,548	6.94	2.80	2,041
Bachiller Experimental (Reforma de la Enseñanza Media - REM)	High-school diploma (1986 educational reform)	7.77	2.26	32	8.21	2.37	23	6.64	1.51	9
Bachillerato LOGSE	High-school diploma (1990 educational reform)	6.59	4.39	17	9.34	6.58	6	5.09	1.48	11

Table A1.1
Summary statistics for net hourly earnings by education cells *(Continued)*

Full sample					Men			Women		
Educational Groups (Spanish Classification)	Equivalence with ISCED[(a)]	Mean	St.D.	N	Mean	St.D.	N	Mean	St.D.	N
Formación profesional de grado medio	*Upper secondary education (Technical school)*									
Sin especificar	Not specified	9.55	5.50	195	10.23	5.77	155	6.88	3.14	40
Oficialía industrial	Industry studies	9.30	2.93	775	9.36	2.94	746	7.69	1.78	29
Formación profesional de 1er grado (FP I)	Lower-vocational and training education	7.35	3.02	3,586	7.89	3.10	2,660	5.80	2.10	926
Ciclos formativos de grado medio de FP	Intermediate professional training	9.65	4.14	103	10.57	4.61	60	8.38	3.00	43
Módulos profesionales de nivel II	Training modules (level II)	7.79	2.90	26	8.20	3.14	19	6.68	1.90	7
Ciclos formativos de grado medio en artes plásticas y diseño	Intermediate professional training - Design and plastic arts	7.27	2.45	16	7.38	2.23	10	7.10	2.99	6
Certificado de aptitud en escuelas oficiales de idiomas	Diploma in languages	8.87	4.69	16	10.39	6.71	6	7.95	3.03	10
Primer nivel de mandos intermedios	First level of intermediate managing	8.31	1.22	8	8.31	1.21	6	8.29	1.77	2
Capacitación agraria	Agricultural training	9.64	3.70	9	9.64	3.70	9			
Peritaje mercantil	Business studies	12.86	6.39	552	13.30	6.60	468	10.42	4.29	84
Formación profesional de grado superior o equivalente	*Post-secondary non-tertiary education*									
Sin especificar	Not specified	11.33	2.48	900	11.45	2.42	855	9.01	2.55	45
Formación profesional de segundo grado (FP II)	Upper-vocational and training education	8.03	3.40	6,400	8.55	3.53	4,815	6.43	2.34	1,585
Ciclos formativos de grado superior en FP	Upper professional training	9.30	4.21	122	10.06	4.48	92	6.96	1.78	30
Ciclos formativos de grado superior de artes plásticas	Upper professional training in plastic arts	8.38	2.74	17	9.51	2.81	11	6.30	0.53	6
Módulos profesionales de nivel III	Training modules (level III)	9.26	3.60	32	10.01	3.93	23	7.34	1.39	9
Maestría industrial	Upper industry studies	10.48	4.69	1,249	10.50	4.70	1,241	8.25	2.47	8
Graduado en artes aplicadas y oficios artísticos	Graduate in applied arts and artistic trades	7.94	3.70	36	8.91	3.61	28	4.54	1.18	8
Titulaciones propias de Universidades de menos de 2 años que no sean de postgrado	Non post-graduate university studies with less than 2 years	10.04	3.98	19	10.51	4.02	16	7.51	3.17	3

Table A1.1
Summary statistics for net hourly earnings by education cells *(Continued)*

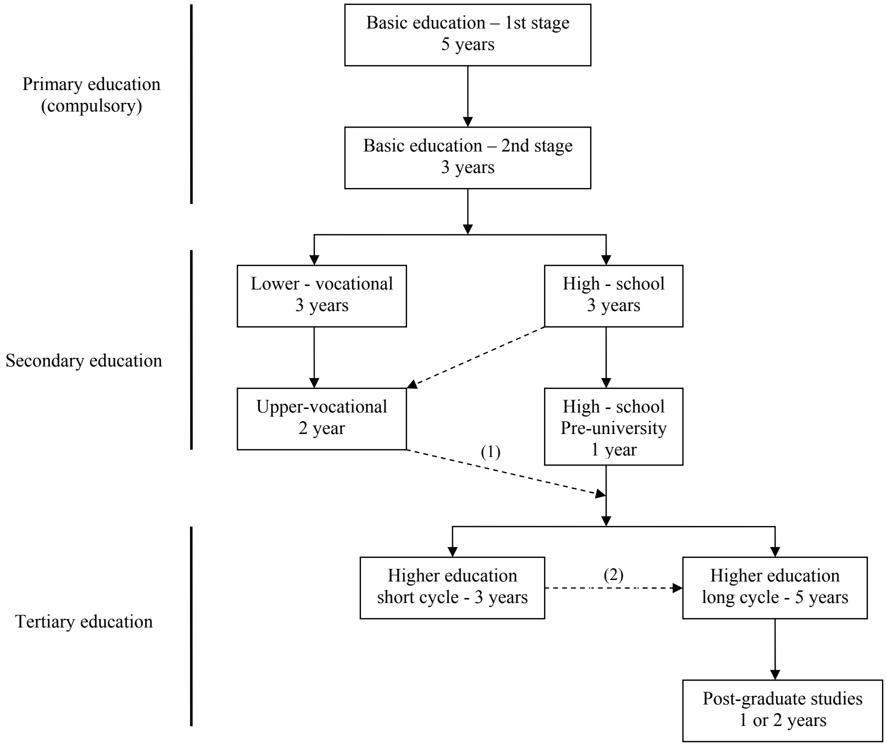
Full sample					Men			Women		
Educational Groups (Spanish Classification)	Equivalence with ISCED[(a)]	Mean	St.D.	N	Mean	St.D.	N	Mean	St.D.	N
Diplomados universitarios o equivalentes	*First stage of tertiary education*									
Sin especificar	Not specified	11.69	5.63	263	12.43	5.74	214	8.45	3.67	49
Diplomados universitarios	University graduate (short cycle - 3 years)	10.63	5.25	2,878	11.78	5.56	2,015	7.94	3.09	863
Ingenieros y arquitectos técnicos	Engineering, architecture (short cycle - 3 years)	13.59	7.72	2,266	13.73	7.76	2,203	8.78	3.56	63
Tres cursos aprobados de una licenciatura, ingeniería y arquitectura	3 complete years of tertiary education (not graduated)	10.67	5.72	109	11.37	6.05	87	7.91	2.86	22
Técnicos de empresas y actividades turísticas	Graduate in business and tourism	9.68	5.94	227	11.56	6.95	126	7.34	3.09	101
Intendentes mercantiles	Business and trade	15.79	3.20	8	15.79	3.20	8			
Títulos propios las universidades de 3 años más años que no sean de postgrado	Non post-graduate university studies with less than 3 years	9.52	4.34	26	9.87	4.50	23	6.86	0.65	3
Licenciados, Ingenieros y arquitectos o equivalentes	*Second stage of tertiary education*									
Sin especificar	Not specified	14.45	6.34	174	15.47	6.33	138	10.54	4.74	36
Licenciados universitarios	BA (Humanities and arts / social sciences, business and law/ sciences)	13.41	8.55	4,976	14.52	9.26	3,695	10.22	4.84	1,281
Ingenieros y arquitectos técnicos	BA (Engineering and architecture)	16.73	7.95	1,051	16.97	7.99	1,007	11.33	4.46	44
Arte dramático	Dramatic arts	16.04	7.03	84	16.41	7.05	79	10.24	3.58	5
Actuarios de seguros	Actuary and insurance	12.86	8.99	7	12.86	8.99	7			
Doctores y postgrado	*PhD and post-graduate education*									
Doctorado	PhD	18.13	8.55	65	19.72	8.62	51	12.31	5.26	14
Especialización para licenciados	Specialization for university graduates	13.30	6.40	16	13.49	6.72	14	11.96	4.89	2
Otros estudios de postgrado propios de la universidad	Other post-graduate studies	11.84	8.13	7	14.32	8.49	5	5.64	0.55	2
Total		8.12	6.82	109,325	8.57	7.41	87,269	6.31	3.07	22,056

(a) The equivalences with the ISCED are exact only for the broad educational levels in bold. The educational groups within each ISCED educational level do not have any equivalence with the ISCED or any other international classification system. Most of the educational groups within each ISCED education level are the same "type" or "level" of education but under different educational reforms. For example, the secondary educational level received different names under the different educational reforms: it was called B.U.P by the 1970 reform, R.E.M by the 1986 reform, and L.O.G.S.E. by the 1990 reform. (b) We only show the educational groups that contain more than 6 observations.

Appendix A2: The Spanish educational system after the 1970 reform

Throughout the last four decades the Spanish educational system has experienced several reforms. These reforms occurred in 1970, 1990 and 2002. In 2005, the government proposed a draft bill to reform the educational system. If approved, it will come into force in 2006. Given that most of the individuals in our sample have attained their education over the period 1970-1990, in this appendix we briefly describe the educational system introduced by the 1970 reform (see Figure A2.1).

FIGURE A2.1
The Spanish education system according to the 1970's educational reform



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

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Resumen

En este artículo utilizamos datos españoles para estudiar el efecto de la variabilidad y la asimetría salarial sobre los salarios individuales. En conformidad con la evidencia previa, en España también observamos una relación positiva entre el riesgo asociado a las elecciones educativas y su rendimiento salarial. Este resultado se encuadra dentro de las preferencias de los individuos aversos al riesgo con aversión al riesgo absoluta decreciente. Nuestro análisis está exclusivamente basado en la elección del nivel educativo, en vez del nivel educativo y la ocupación conjuntamente. Esto supone en si mismo una mejora sustancial respecto a la evidencia anterior.

Palabras clave: Aversión al riesgo, preferencia por la asimetría, elección educativa, compensación salarial.

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