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Departamento de Economía
Universidad Carlos III de Madrid
Calle Madrid, 126
28903 Getafe (Spain)
Fax (34) 916249875

Students' assessment of higher education in Spain†

César Alonso-Borrego*
Universidad Carlos III de Madrid

Antonio Romero-Medina
Universidad Carlos III de Madrid

Abstract

We explore evidence on the perceived economic value of higher education to college students in terms of their reported expected and shadow wages. Our estimates provide predictions for expected wages that are similar across gender and become closer to actual wages as students approach graduation. This is consistent with an improvement in the quality of student information used to forecast wages. Shadow wages relative to expected wages increase during the academic year for men and are constant for women, which is consistent with the higher reluctance of women to drop out of university. Finally, students with lower socioeconomic background and poor performance exhibit a higher propensity to drop out.

Journal of Economic Literature Classification Numbers: I23, J24, J31, C24, C25.

Keywords: university education, subjective valuation, wage expectations, shadow wages, ordered response.

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* Corresponding author. Department of Economics, Universidad Carlos III de Madrid, 28903 Getafe, Spain. Fax: +34-91-6249875. e-mail: cesar.alonso@uc3m.es.

1 Introduction

Spain has experienced a sharp growth in the population share with higher education since the 1980s (San Segundo, 1997). Having started as a country with relatively low educational attainment, the percentage of young people with higher education is currently fairly close to that in the US and is above the OECD average. However, international comparisons suggest that this massive increase in participation in higher education is accompanied by significant imbalances. In particular, the increase in higher education attainment is primarily observed for university degrees, whereas non-university higher technical education, aimed at skilled blue collar jobs, has been disregarded (see Fina et al., 2000; Petrongolo and San Segundo, 2002, among others). Moreover, there is an excess of long-degree graduates and a lack of short-degree graduates (San Segundo, 2002; Salas Velasco and Martín-Cobos Puebla, 2006)[1]. These imbalances may decrease the returns on college education in Spain compared to other OECD countries, thus discouraging young people from entering higher education.

This paper contributes to the ongoing debate by using micro data on students' self-reported economic value of higher education. In particular, we use a survey of Spanish college students conducted in 2001, 2004 and 2005 to investigate their own monetary valuation of a university degree. We analyze their answers on the wage they expect to earn after completing their degree, as well as the shadow value that they assign to their studies. This unique information allows us to focus on two distinct issues related to the problem of career choice. First, we can explore the reported economic value of a college degree by active college students, conditional on family background and personal and academic characteristics. Second, we can assess to what extent self-reported measures of expected and shadow wages are realistic by comparing them with average actual wages for employees with higher education.

Since the survey wage variables are ordered categorical variables, whereby respondents are offered a choice among several monetary intervals, our baseline econometric model consists of a discrete ordered choice model in which the thresholds correspond to known monetary values. Unlike an ordered response model with unknown thresholds, we can identify the scale of estimated parameters and thus obtain predictions of individual wages.

[1] We denote *licenciaturas* and *ingeniero superior*, which take five academic years or more, as long degrees. We denote *diplomaturas* and *ingeniero técnico*, which take three or four academic years, as short degrees.

Furthermore, we also check the potential attrition bias in wages and university studies due to non-response, finding that the reasons for non-response are fairly exogenous with respect to the wage determination models.

We estimate models for both expected and shadow wages, considering two different subsamples according to the time for degree completion. Namely, we consider college students in their first and penultimate degree years. Our data set contains information about the degree and academic year for each student, as well as gender, pre-university and college academic performance, and socioeconomic background. We also include individual information on degree choice by each student before entering university, and additional reasons behind their degree choice.

Regarding expected wages, the most recent academic performance of the student appears to be the major determinant. The predictions obtained from the model reveal higher expected wages for students closer to graduation. With respect to shadow wages, our results are in agreement with a simple model of investment in college education. In addition to academic performance, factors related to family characteristics, among others, have a substantial effect on shadow wages. Unlike males, we find that for females the shadow wage relative to expected wages does not change with degree year, reflecting their higher relative reluctance to drop out of university.

The remainder of the paper is organized as follows. In Section 2 we describe a simple human capital investment model and define the variables of interest to show the economic value of a college education from the point of view of the student. Section 3 outlines the data set, the variables, and alternative model specifications. Sections 4 and 5 present the econometric framework and our estimation results. Section 6 provides some concluding remarks.

2 Theoretical framework

We use a stylized model of human capital accumulation and investment in education that suits the needs of our empirical analysis based on Trostel (2004). For any individual, we assume that her individual wage, W^*, is proportional to her amount of human capital,

H:[2]

$$W^* = rH, \tag{1}$$

where r is the user's cost of human capital. The amount of accumulated human capital H is assumed to be determined through the following production function:

$$dH_t/dt = \varphi x_t^{\alpha} y_t^{\gamma} H_t^{\delta}, \tag{2}$$

where, at time t, x denotes the amount of time invested in human capital, y represents those goods used in producing human capital, such as training services, physical capital, etc.; and φ is a parameter representing individual productivity or capacity. Finally, α, γ and δ denote the elasticities associated with each of the aforementioned variables. For simplicity, and given that it is irrelevant for our analysis, we disregard the depreciation of human capital. To focus on interior solutions, we impose that $\alpha + \gamma < 1$.

Following Haley (1976), first-order conditions for optimal production can be replaced in the production function. Then the previous equation becomes:

$$dH_t/dt = \Phi x_t^{\sigma+\gamma} H_t^{\delta+\gamma}, \tag{3}$$

where

$$\Phi = \varphi \ (yr/\alpha p)^{\gamma}, \tag{4}$$

and p is the price of y. Since we are primarily concerned with human capital creation through education, the amount of human capital created is measured in years of education. Assuming that each year of education has the same impact on human capital accumulation over time, and given that x remains constant, the previous equation can be simplified. Without loss of generality, we can then consider $x = 1$ so that

$$dH_t/dt = \Phi H_t^{\sigma} \tag{5}$$

for $0 < t < S$, where $\sigma = \delta + \gamma$, i.e., the elasticity of inputs can be accumulated. The equation associated with the production function for human capital is a Bernoulli equation

[2] In other contributions, such as Blinder and Weiss (1976) and Rosen (1976), among others, an alternative, but essentially equivalent, definition is proposed, whereby the production technology of human capital is linearly related to wages, although its productivity exhibits a non-linear relationship.

with constant coefficients. Denoting S as the total amount of education measured in years, the solution to this equation after S years of education is:

$$H_S = \begin{cases} H_0 e^{\Phi S} & if\ \sigma = 1 \\ (H_0^{1-\sigma} + (1-\sigma)\Phi S)^{1/(1-\sigma)} & if\ \sigma \neq 1, \end{cases} \tag{6}$$

where H_0 is the stock of human capital before schooling. If individual human capital before and after schooling were observed, the hypothesis that the input elasticity σ is equal to one could be tested for. In general, a lack of data impedes testing such a hypothesis, which is usually imposed by assumption. Under such conditions, substituting H_S in the relation between wages and human capital, $W^* = rH$, and taking natural logarithms, we obtain a linearized expression that provides an empirical relation between the logarithm of wages and years of higher education:

$$\ln W^* = \ln r + \ln H_0 + \Phi S. \tag{7}$$

Since human capital before schooling is a function of individual factors, such as ability, family and socioeconomic background, some of which are captured by observable factors, Z, we parameterize H_0 as:

$$H_0 = \exp(\theta_0 + \boldsymbol{\theta}_1' \mathbf{Z} + v), \tag{8}$$

where v captures individual unobservable factors not captured by Z. Assuming that the user's cost of human capital r is constant, and using i to index individuals, the specification becomes:

$$\ln W_i^* = \alpha + \Phi S_i + \boldsymbol{\theta}_1' \mathbf{Z}_i + v_i. \tag{9}$$

2.1 Expected wages

The equation above, which posits a simple linear relation between observed individual wages and schooling, allows us to obtain the average expected future wages of college students under some additional assumptions. Assuming, without loss of generality, that unobserved individual factors are on average equal to zero, the expected log wage for a level of education S and a given set of observed individual factors equal to Z is $\alpha + \Phi S + \theta_1' Z$.

Moreover, for a university student in the k-th academic year of her college degree, her expected wage after graduation will depend on the information set determining her expectation. In particular,

$$E_k(\ln W^*) = \alpha_k^e + \Phi_k^e S + \boldsymbol{\theta}_{1k}^{e\prime}\mathbf{Z} + E_k(v), \tag{10}$$

where $E_k(\bullet)$ represents the mathematical expectation, conditional on her information set, and α_k^e, Φ_k^e, $\boldsymbol{\theta}_{1k}^e$ represent the expected returns in the wage equation of the corresponding variables in that information set. Assuming that $E_k(v)$ is equal to zero, then the expected average wage becomes $\alpha_k^e + \Phi_k^e S + \boldsymbol{\theta}_{1k}^{e\prime}\mathbf{Z}$.

Therefore, the differential between average expected wages and average actual wages arises from the differences between the expected and actual returns of each variable,

$$[E_k(\ln W^*) - E(\ln W^*)] = (\alpha_k^e - \alpha) + (\Phi_k^e - \Phi)S + (\boldsymbol{\theta}_{1k}^e - \boldsymbol{\theta}_1)'\mathbf{Z}. \tag{11}$$

Note that this differential ultimately depends on the distribution of information across students. Student information sets are related to the amount and quality of a student's knowledge about the economic value of her college degree, and to the time until receiving a wage as a graduate, i.e., her prediction horizon. We thus expect that the gap between expected and actual wages would be greatest at the beginning of a university course and would decrease as the student approaches graduation.

2.2 Shadow wages

We define as shadow wage the minimum real wage for which a student would be willing to drop out of university in exchange for a job during her entire labor life.[3] Decisions to drop out are not only a function of the shadow wage, as dropouts stop bearing the fee and time costs of achieving higher education.

Considering that retirement age occurs during period n, assuming a discount factor r, we can formally define the corresponding shadow wage w^s for a student leaving college s years after entering as:

[3] Given the way in which college students were asked about their shadow wages, it is understood that the discounted real wage will remain constant over time.

$$w^s = \frac{W_s + \sum_{t=s+1}^{n} (1+r)^{-(t-s)} W_t}{n-s}.$$

If, instead of the stream of future wages, we consider the difference between cumulative wages in a lifetime with and without an investment in human capital G, we have:

$$v^s = \frac{G_s + \sum_{t=s+1}^{n} (1+r)^{-(t-s)} G_t}{n-s},$$

where v^s is the actual value of the investment in human capital G. This value has to be greater than zero and by solving the equation for v^s we can compute the maximum interest rate to be paid for financing such human capital investment.

Our model provides two predictions relative to shadow wages. First, if real wages increase with on-the-job experience at a rate that offsets further education years, the expected wage after graduation must be lower than the shadow wage. Second, as far as the returns to university education are positive, the shadow wage must increase with years of college education.

3 Data

3.1 The survey

The primary source of data is a survey financed by the Madrid regional authority and carried out in the academic years 2000/2001, 2003/2004 and 2004/2005. The survey explored attitudes and opinions with regard to the higher education system of young students registered in public universities in the Madrid region. The survey design is based on a nationwide data set produced jointly by the Centro de Investigaciones Sociológicas (National Sociological Institute) and the Ministry of Education in 1990, known as "Los jóvenes ante la Universidad" ("Young people facing college education").

The innovation of our data set lies in two unique questions that are central to our research, which refer to wages expected after graduation and shadow wages. Regarding expected wages, each student is asked how much she believes her monthly wage will be after concluding her studies: "What is the monthly wage that you are expecting

after graduating?". The answers provided by students are discretized into five ordered categories, in addition to no answer and "Don't know". These categories are: between 450 and 901 euro; between 901 and 1803 euro; between 1803 and 3606 euro; between 3606 and 5409 euro; and more than 5409 euro. With respect to shadow wages, the question is: "What is the minimum monthly wage at which you would leave university in exchange for an indefinite contract with that real wage for your whole labor lifetime?" The response categories are the same as for expected wages.

In Table 1, we show the marginal relative frequencies of expected and shadow wages for each wage category in our sample. Expected wages exhibit a remarkable unimodal profile, whereby 53 percent of students chose the third category (between 1803 and 3606 euro per month). On the contrary, the sample shadow wages are distributed much more uniformly for all categories above the minimum of 450 euro, although there is a substantial level of right censoring, with 37 percent of students choosing the upper category. Despite these differences in the empirical distributions of expected and shadow wages, there is a strong positive rank correlation between the variables, with a Kendall coefficient of ordinal correlation of 0.28 and the corresponding p-value below 0.01 percent. Unfortunately, approximately one-third of students provided no answer or declared "Don't know".

Our data set also contains information on gender, academic and personal status, and socioeconomic background for each student. For the latter, there are data on parents' education, their labor market status, and their income. The academic information provides details on secondary studies completed by the respondent, the ranking of alternative university studies considered, university studies actually followed, and college performance. Information on secondary (pre-university) studies includes details such as whether the secondary academic center was public or private (Public secondary), if the science field of specialization was attended (Science secondary), the examination grade needed to access university (Access grade), and whether this examination was passed at the first attempt (Access at first attempt). In terms of alternatives considered, respondents had to provide a prioritized list of alternative colleges within the Madrid university district and in Spanish universities outside of Madrid considered. We included information on whether the respondent also applied to colleges outside the Madrid university district (External choices) and whether her first three choices featured a particular degree that could be chosen in several universities (Same degree) or different degree courses in a particular university (Same university). Data on university studies included details on whether the

course was the student's first choice (First choice), a long or a short degree, a Science degree, or a joint degree leading to two university diplomas for two different disciplines.

Information on college performance includes the degree year of the course, whether the student has failed and thus repeated an academic year (Repeater), whether she was granted a scholarship (Grant), and whether she is working (Work) and/or searching for a job.

Descriptive statistics of the main variables are provided in Table 2. Nearly 60 percent of the respondents were women. Concerning family characteristics, approximately 20 percent reported that they belonged to a high-income household. Information on the educational level of parents is collected in eight categories: illiterate, below primary, completed primary, professional high school, lower secondary, complete secondary, short university degree, and long university degree. We find that the educational levels of parents are highly correlated: the t-statistic for linear regression of mother's education vs. father's education is 28.72, with a Kendall statistic for ordinal correlation of 0.46 and a p-value of less than 0.001 percent. We thus concentrate on the educational level of the fathers, in particular, whether the father has a university degree (University father). The percentage of respondents whose father achieved a university degree (long or short) amounts to 41 percent of the sample.[4]

Nearly 60 percent of the students undertook secondary studies in a public high school, and approximately half followed a science field of specialization in secondary education. In terms of access grade (average examination grade achieved in secondary education, which in our sample was truncated at 50) the minimum score required to enter university was 68 points on average, and 84 percent of the respondent passed the access examination at their first attempt. With regard to alternative colleges considered, approximately 22 percent of students also applied elsewhere, 15 percent considered the same degree offered in different colleges, and only 7 percent prioritized a particular university.

Approximately 60 percent of the sample students are following courses corresponding to their first choice. Long degrees clearly dominate, accounting for 80 percent; of these,

[4] The remaining parental educational levels correspond to between 10 and 18 percent of respondents, except for the two lower levels, which jointly account for 15 percent of the sample. Compared to the Spanish population as a whole, the educational level of sample fathers is slightly above the average educational level of Spanish parents with children of university age. This same result is observed if we consider maternal education. This bias is coherent with the pervasive intergenerational inertia in educational levels within the same family.

approximately 40 percent correspond to science disciplines. The proportion of students following a joint degree is very small. The performance of college students in our sample can be summarized as follows. Less than 20 percent were awarded a grant; nevertheless, it must be noted that grants are awarded for economic reasons if a minimum academic performance is accomplished. Approximately 30 percent of the students have failed and repeated at least one academic year, and one-fifth of them reported that they are satisfied with their studies. Finally, nearly 20 percent are also working (including full-time and part-time work).

Splitting the sample statistics by gender reveals differences in family income; the percentage of students belonging to high-income households is clearly lower for females than for males. However, the major differences between men and women are related to academic performance. Concerning pre-university performance, a higher percentage of women passed the access examination at their first attempt, and a higher proportion of women are following degrees in colleges that were their first choice. Women also seem to perform better at college, with a higher proportion of grants awarded, a lower proportion of repeaters, and a greater proportion reporting satisfaction. This preliminary information thus provides evidence that female students are somewhat different than male students, particularly in terms of academic performance. Nevertheless, the information in Table 2 only allows comparison of sample averages, and the differences are not significant in many cases. Besides, a conditional analysis is needed to provide a proper account of these apparent differences.

3.2 Complementary data

We complement the information from our primary data source with the Survey of Wage Structure, carried out by the National Institute of Statistics (INE hereafter, which is the Spanish acronym) to investigate the structure and distribution of wages in Spain for a variety of variables such as age, sex, education level, and region of residence. For comparison with our primary data evidence, we use 2002 wage data.

The average monthly wage for dependent employees aged 20–29 years is shown in Table 3. Since this information is widely publicized and easily accessible, it is reasonable to assume that it is part of the information set that university students used when computing their expected wages. Nevertheless, it must be noted that the average wages in

this complementary data set are representative of the population that voluntarily decide to work at market wages, and therefore such information is potentially affected by two sources of selection bias. The first source is related to the decision on labor participation, which differs for women and men. In the age range 20–29 years, females exhibit a lower participation rate than men. The second source arises from the fact that the Wage Distribution Survey reports wage earnings for dependent employees, and therefore is restricted to those who decide to be wage earners. However, it is not possible to control for these sources of sample selection, since both participation decisions take place after graduation and may thus be conditional on events that take place after the survey. In any case, we use the data in Table 3 as a benchmark to evaluate expected and shadow wages of college students in our sample.

Analysis of the data in Table 3 reveals three remarkable findings. First, there is a positive correlation between educational level and earnings. Second, average earnings are greater for men than for women. Third, employees in the Madrid region enjoy earnings above the national average. This is true for all educational levels and both genders, but the differential increases with the level of education. Differences in the cost of living and in job characteristics (industry, occupation) account for these differentials.

Empirical evidence on the positive correlation between education and earnings, irrespective of place of residence and gender, matches one of the major predictions of the theoretical framework in Section 2. This effect may partly reflect the fact that individuals who are more able to undertake both academic and professional tasks are more motivated to invest in education, and their return to education may be above average. Our data do not allow us to control for this potential bias; we assume that the distribution of unobserved capabilities of the students interviewed do not differ from the analogous distribution in the Survey of Wage Structure.

In Table 4 we present the differential returns to long university degrees for lower educational levels in the Madrid region. The average wage differential between those with a long university degree and those without any university degree is approximately 60 percent. Nevertheless, this differential does not capture the average wage differential per further year of education in the life cycle for two reasons. First, on average, the greater the years of education for an individual, the higher is his age of entry into the labor market, since many individuals do not enter the labor force until they have completed their studies. Second, university degrees differ in the number of academic years required for completion,

so that some are shorter than four years whereas others may be longer than five years. In the upper panel of Table 4, we find that the wage differential between graduates with a long degree and those with a short degree, is much lower than the differential between long-degree graduates and non-graduates. In the lower panel of Table 4, we show the same differential returns corrected for the number of years needed to complete each education level. The adjusted returns for long-degree male and female graduates, respectively, are 7.3 and 4.8 percent for those with secondary education, and 10.8 and 9.6 for those with a technical secondary education.

A gender wage differential is evident for all educational levels, but it decreases with increasing education level. In more detail, there is a positive differential for males that ranges between 15 and 20 percent. Among the potential reasons for the gender gap, we should mention three: pure gender discrimination; the possibility that, with all other things equal, firm-specific accumulated human capital tends to be lower for women because they are more likely to experience discontinuities in their professional career; and occupational segregation. In the latter case, women are more likely to face restrictions that force them to choose occupations with lower wages in exchange for non-wage compensations such as greater time flexibility.

4 Econometric framework

4.1 Basic model

Our reference specification is Equation (9) in Section 2, which features the actual wage conditional on the individual's level of education, personal characteristics, and socioeconomic background:

$$\ln W_i^* = \alpha + \Phi S_i + \boldsymbol{\theta}_1' Z_i + v_i \qquad (i = 1, \ldots, n). \tag{12}$$

Nevertheless, unlike the objective information provided by actual wages observed for working individuals, we focus on the subjective valuation that the college students reported for their university education. This subjective valuation provides two different values: the expected wage, i.e., the wage that each student expects to earn as an outgoing graduate; and the shadow wage, which is the minimum wage for a labor lifetime job for which the

student would be willing to drop out of college without graduating. These data on expected and shadow wages reported by the college students allows us to analyze the value of university education that college students attribute to higher education.

As already mentioned in Section 3, the students surveyed differed in their academic and personal information and in their degree year, so that there is individual heterogeneity in their levels of human capital accumulation and other individual characteristics. Such heterogeneity affects the individual computation of expected and shadow wages. In particular, with all other things equal, differences in the degree year, which reflect the time to completion, affect the student's opportunity cost of education, as well as the amount and quality of her information. These differences may thus lead to differences in subjective valuation of the same college studies. To account for this, we distinguish among two different groups according to the time for degree completion: college students in their first and in their penultimate degree years. Using this breakdown, the years of education for each group can be taken as constant, and therefore ΦS_i will be part of the constant term for each group.

In addition to the variables that characterize socioeconomic background and may be associated with human capital accumulated before higher education, it is also important to account for further individual characteristics. In particular, gender and the academic curriculum during secondary education may have a systematic effect on the subjective valuation of wages. Thus, we extend the vector of covariates, denoting it as $\mathbf{X}_i$. In addition to unobservables affecting human capital obtained before higher education, there are individual characteristics that are unobserved in the data that affect subjective valuations. Therefore, we can write our empirical model as:

$$\ln W_i^* = \boldsymbol{\beta}'\mathbf{X}_i + u_i. \tag{13}$$

If W_i^* were observed, appropriate estimates of $\boldsymbol{\beta}$ could be obtained through OLS under certain conditions. However, we have emphasized in Section 3 that we do not fully observe W_i^*, but a discretized version of it, W_i, that can be defined as:

$$W_i = j \text{ if } \mu_{j-1} < W_i^* < \mu_j \quad (j = 1, \ldots, 5), \tag{14}$$

where the values μ_j, $j = 1, \ldots, 5$ are known. We can also define indicator variables for

each category as:

$$d_{ij} = 1(W_i = j) = 1(\mu_{j-1} < W_i^* < \mu_j) \quad (j = 1, \ldots, 5). \tag{15}$$

The censored nature of the observed dependent variable W_i invalidates OLS as an estimation method. We address this problem using the strategy developed for models with multiple ordered responses that has been applied when using contingent-type data as, for example, in Cameron and Quiggin (1994), Cai, Deilami and Train (1998), and Papke (1998). Our empirical model is thus an ordered response model, yet in our case the thresholds determining the different categories are known, so there is no need to estimate them as parameters.

Even though the observed variable W_i is ordinal, knowing the cutoff points implies that no normalization is required to identify the vector $\boldsymbol{\beta}$ and the likelihood function will generally depend on both $\boldsymbol{\beta}$ and $Var(u_i|\,\mathbf{X}_i) = \sigma^2$. Maximum likelihood estimation can be carried out after assuming a distribution for u_i, $F(.)$. The probability that respondent i chooses wage category j is:

$$\begin{aligned} \Pr(W_i &= j|X_i) = \Pr(\mu_{j-1} < W_i^* < \mu_j) && (16)\\ &= \Pr(\ln \mu_{j-1} < \ln W_i^* < \ln \mu_j) && (17)\\ &= F(\ln \mu_j - \boldsymbol{\beta}'\mathbf{X}_i) - F(\ln \mu_{j-1} - \boldsymbol{\beta}'\mathbf{X}_i). && (18) \end{aligned}$$

Then the log-likelihood takes the form:

$$\ln L(\beta, \sigma) = \sum_{i=1} \sum_{j=1} d_{ij} \ln \Pr(W_i = j|\,\mathbf{X}_i).$$

Given our knowledge of thresholds, we can obtain projections for expected wages and shadow wages as in a standard linear model. Note, in contrast, that if the cutoff points were not known, the parameter vector would only be identified up to a normalization. In such a case, it is usually assumed that $\sigma = 1$ and, therefore the scale of $\boldsymbol{\beta}$ conveys no information.

4.2 Potential selection bias

The fact that a significant proportion of respondents failed to declare their expected or shadow wages and their university degree leads to a potential sample selection problem (cf. Heckman, 1979). If the unobserved effects in the respondents' wages, u_i, are correlated with random factors affecting the probability of answering the wage question in the survey, then using only the subsample of individuals who declare their wages will produce inconsistent estimators. To evaluate the incidence of this potential bias, we analyze a sample selection model in which, in addition to our wage equation, we considere an auxiliary model to account for a respondent's decision to declare her wages and her university course, represented by a binary variable, D_i, that equals 1 if the respondent decides to give an answer and 0 otherwise. We further assume that the respondent decides on whether to declare her wage or not on the basis of a score equation that is a linear function of characteristics of which only some are observed in the data set. In particular,

$$D_i = \mathbf{1}(\boldsymbol{\gamma}'\mathbf{Z}_i + \varepsilon_i > 0), \tag{19}$$

where $\mathbf{1}(\cdot)$ is a binary indicator that equals 1 if the condition in parentheses is true and 0 otherwise; $\boldsymbol{\gamma}'\mathbf{Z}_i$ and ε_i capture observed and unobserved characteristics determining the decision on whether to declare an answer. The unobserved term ε_i is assumed to have a known cumulative distribution $F_\varepsilon(.)$ that is symmetric around 0, so that the probability that respondent i declares her wage is $F_\varepsilon(\boldsymbol{\gamma}'\mathbf{Z}_i)$.

To account for potential selection bias, we reparameterize Equation (13) as:

$$\ln W_i^* = \boldsymbol{\beta}'\mathbf{X}_i + \rho\varepsilon_i + \zeta_i, \tag{20}$$

where ρ represents correlation between the unobserved terms associated with selection Equation ε_i and wage Equation u_i, with $Var(\varepsilon_i|\mathbf{Z}_i) = \sigma_\varepsilon^2$. Under this new parameterization, we assume an orthogonal decomposition of the unobserved part of the wage equation in two terms, one that is perfectly correlated with the unobserved part of the binary decision on whether to declare a wage value, and an independent random error. The probability that respondent i chooses category j can then be written as:

$$
\begin{aligned}
\Pr(W_i = j \,|\, \mathbf{X}_i, \varepsilon_i) &= \Pr(\mu_{j-1} < W_i^* < \mu_j) && (21)\\
&= \Pr(\ln \mu_{j-1} < \ln W_i^* < \ln \mu_j) && (22)\\
&= F(\ln \mu_j - \boldsymbol{\beta}'\mathbf{X}_i - \sigma_\varepsilon \varepsilon_i) - F(\ln \mu_{j-1} - \boldsymbol{\beta}'\mathbf{X}_i - \sigma_\varepsilon \varepsilon_i). && (23)
\end{aligned}
$$

A non-significant estimate of ρ would imply that, with regard to the wage equation model, the sample selection associated with declaration of a wage value or not is exogenous. In such a case, we could estimate the wage equation by ignoring sample selection at no consistency cost. We have estimated a sample selection ordered probit model by maximum likelihood using the subroutines written for Stata by Miranda and Rabe-Hesketh (2006). Unfortunately, estimation of this type of model is computationally very demanding. Besides, concavity of the likelihood function is not guaranteed, so that convergence cannot be achieved in the presence of a moderately low number of covariates. Thus, we have estimated simplified versions of our wage specifications with sample selection.

In either case, our estimates (not reported here) do not provide evidence against the null hypothesis that sample selection was exogenous. This result suggests that conditioning on the subsample of students with non-missing expected wage values does not bias our estimates. Therefore, we can proceed to estimate the expected wage equation using such a subsample without controlling for sample selection. We thus estimated our specifications for expected and shadow wages disregarding the potential attrition bias due to non-response for wages and university studies.

5 Results

In this section, we analyze the valuation of university studies by college students in the Madrid region as measured by their expected and shadow wages. Our estimates can be subsequently used to compute individual predictions of both expected and shadow wages for comparison with average actual wages for graduates working in Spain and in Madrid.

It must be recalled that values reported for expected and shadow wages represent subjective valuations. In the case of expected wages, this means that interpretation of the effects of the conditioning variables is unclear. Such effects combine the influence of

these variables on the potential actual wage, on the one hand, and the information quality used in computing wage expectations, on the other.

Regarding the shadow wage, we are concerned with the extent to which family background, academic performance, and the degree year, among other things, affect the income required to prompt a student to drop out of university. Analysis of the shadow wage is of double interest. First, we can learn about the permanent income predicted by college students after entering the labor market as graduates, and how such permanent income affects their degree choice. Second, given the students' expectations about their permanent income—and their expected wage—after graduation, we can assess whether their estimates of future economic prospects are realistic compared to actual wages.

5.1 Expected wages and university education

To account for the degree year of the respondents, we estimate separately for two different subsamples: first degree year and penultimate degree year. We would expect the effects of the conditioning variables to differ very much for these two particular groups, which correspond to extreme cases of the time to graduation. Namely, we would expect students closer to completion to have much lower uncertainty about their academic prospects, as well as a better knowledge of their job market prospects after graduation.

Expected wages are censored into five wage categories, with the highest category being unbounded to the right. Given that we observe wage thresholds, the scale of the parameters is identified. Thus, the variance of the error term can be estimated, together with the remaining parameters of interest, by maximum likelihood. Moreover, although both the ordered probit and pointwise censored models are consistently estimated by maximum likelihood, the latter is more efficient as it exploits the information available on monetary thresholds in the questionnaire.[5]

The maximum likelihood estimates for expected wages for students in their first year and penultimate year are reported in Tables 5 and 6, respectively. In each case, we report

[5] An important practical advantage of exploiting wage thresholds by means of the pointwise censored model is that we do not need further assumptions about the distribution of the right tail to compute individual expected wages. More precisely, in an ordered probit in which the information on threshold values is not exploited, we must introduce an additional assumption for the right tail of the wage distribution (for declared expected monthly wages above 5409 euro). Using results from the ordered probit estimates, we find that predicted individual expected wages are very sensitive to this additional assumption.

unrestricted estimates in the first column, and we excluded non-significant covariates in the last two columns, showing our preferred estimates in the last column. We concentrate our comments on this final specification. The model adjustment is reasonably good for the two student groups. Given that we introduced different interactions related to the type of university course (Long degree, Science degree, and Long degree in Science), the reference group corresponds to short degrees in non-science disciplines.

Most estimated coefficients in Tables 5 and 6, when significant, show similar signs, except for some qualifications that are detailed below.

Most of the pre-university variables, particularly those related to access grade as a measure of academic performance shortly before university entrance, seem to be relevant in determining the expected wages of first-year college students. Given the parameter values, the net effect of access grade is positive, but is more intense for students who passed the access examination at their first attempt. These variables are non-significant for students in later degree years, as observed in Table 6. For this student group, pre-university performance loses relevance in favor of university performance.

The effect of gender is negative, although it is not significant for first-year students. This effect is slightly positive for later-year female students in science disciplines.

Among family background variables, the high-income dummy is significant and negative for first-year students pursuing short degrees, and is positive but quantitatively smaller for long-degree students. This result is reversed for later-year students. A university graduate father has a positive effect, and is clearly significant for first-year students.

Concerning academic performance (as measured through the variables Repeat, Grant, Satisfied) in university, significant effects are only observed for long-degree students in their penultimate year, with no effect for first-year students. Long-degree students in non-science disciplines who have repeated declared lower expected wages. This negative effect was not observed for long-degree science students. The same is true for students who reported satisfaction with their college studies. Award of a scholarship was eliminated from the final specification owing to its lack of significance.

Finally, as expected, variables without direct influence on the amount of human capital acquired by the student, such as the reason for choosing a university course, are not relevant in the determination of expected wages.

In Table 7, we use our preferred expected wage estimates from Tables 5 and 6 to predict student expected wages. We find that the expected wages for any degree year group are greater than average actual wages for graduate workers aged 20–29 years in Spain, and even in the Madrid region, where wages are higher. Hence, wage expectations tend to be greater than actual wages; in other words, college students tend to overestimate their potential wages. In addition to individual quality effects, the individual covariates also reflect a student's ability to compute expected wages.

Predictions of expected wages are higher for first-year students than for penultimate-year students. Expected wages for first-year women are, on average, lower than those for men in the same group. The fact that expected wages, on average, move closer to actual wages for graduates demonstrates that the formulation of expectations improves as students approach graduation. Finally, the percentage gap is much higher for women than for men, reflecting the wide wage differential by gender. In the case of male students, the differential is substantial for those in their first year and negligible for students closer to completion. On the contrary, the gap between expected and actual wages for female students remains large, even in teir penultimate year, and is smaller for long degrees than for short ones.

The overestimation of expected wages with respect to actual wages for working graduates aged 20–29 years is actually greater than the difference reflected in Table 7, because the individuals in our sample are not strictly comparable with the sample for which average actual wages were computed, which is restricted to graduates aged 20–29 years who have decided to work and have found a job. In contrast, our sample comprises students who have not yet graduated. For those who graduate, a percentage will eventually not work, either because they decide not to enter the labor market or because they will not find a job. Moreover, a proportion of them will drop out of college before graduation. Therefore, it is possible that the apparent improvement in the formulation of expectations with increasing degree years merely reflects sample selection of students who are much more likely to work in jobs that require a university education.

5.2 Shadow wages and university education

We now analyze the determinants of lifetime labor income that university students would accept in exchange for leaving university before graduation. It is worth mentioning that

the fraction of students not declaring a shadow wage is greater than that not declaring an expected wage.

In Tables 8 and 9, we present estimates of the pointwise censored model for first- and later-year students. Our empirical strategy closely follows the previous one for expected wages. Again, the model adjustment is appropriate.

The effect of gender is modest for first-year students and negligible for later-year students. Therefore, any substantial difference in the prediction of shadow wages by gender would arise because of differences among individuals. Among the family background variables, the high-income dummy is positive and significant for the two student groups. However, this effect is minor for students in science disciplines.

Father's education has a positive and significant effect for students in their first and penultimate degree years. This positive effect on expected wages is in accordance with the positive effect of parental education on potential wages. Besides, we would expect the quality of student information used to formulate wage expectations to improve with father's higher education, and therefore students with highly educated parents are less likely to overestimate their expected wage relative to actual wages. These two effects tend to complement each other. The effect of father's education is even higher for students closer to completion.

Concerning pre-university academic performance, grade achieved in the access examination, as a positive indicator of student quality, has a positive effect for first-year students, and failure to pass this examination at the first attempt has a significant and negative impact for all students. Other academic performance variables, such as science specialization in pre-university education, are non-significant for later-year students. However, giving priority to the same degree in different universities has a negative and significant impact in both groups. With regard to university academic performance, having repeated a university year has a negative and significant impact for all students.

Finally, unlike the results for expected wages, the reasons behind degree choice have an impact on shadow wage determination for first-year students. Family tradition and Parental influence exert positive and negative effects, respectively. For later-year students, only college proximity has a negative effect on shadow wages.

In Table 10, we report the average predicted shadow wages. Shadow wages are, on

average, greater for first-year female students and smaller for later-year female students. When comparing average shadow wages with average actual wages for working graduates aged 20–29 years, the relative shadow wage is much greater for women. In Table 11, we report the percentage ratio of shadow wages to expected wages. The pattern is remarkably different by gender, increasing for men and constant for women, in terms of the degree year. The relative shadow wage for females equals, on average, the highest relative shadow wage reported by men. Therefore, women are much more reluctant to drop out of university. Alba-Ramirez and San Segundo (1995) found that whereas the return to primary and secondary education in Spain is lower from women than for men, the relative return to college education is higher for women. Hence, although female graduates are, on average, worse paid than males, women enjoy a higher relative differential return to university education compared to lower educational levels. This result suggests that investment in university education is more attractive for women than for men. It is also consistent with the fact that more women than men have registered for university in Spain since 1986.

5.3 Dropout propensity

According to our model, a student who reports a shadow wage lower than her expected wage believes that her wage profile throughout her working life as a graduate will not compensate for the cost of finishing her studies. Under these conditions, the student is prompted to abandon her studies. In Table 12, we report the number of individuals in this situation in our sample, broken down by degree year. A decreasing pattern for dropout propensity is evident for long degrees. However, the pattern is fairly constant for short-degree studies, which are more focused on technical jobs.

To analyze the factors that influence this behavior, we used a probit model in which a declared shadow wage lower than the declared expected wage was the dependent variable. The results are presented in Table 13. The first column presents results for students excluding those in their last year. In the second and third columns, we report results for students in their first and penultimate year, respectively. The profile that describes potential dropout can be summarized as a student with poor pre-university and university performance, already a part-time student, with relatively low parental human capital and whose parents influenced her college and degree choice.

These findings have policy implications. Wage distribution by education level in Spain is relatively narrow, so that the return to higher education is small relative to other OECD countries. In fact, the dropout rate in Spain is remarkably high, which is mostly attributed to failure of the educational system. Our analysis indicates an alternative explanation. There are economic reasons related to observed variables that can explain, at least in part, the dropout propensity in Spanish universities.

6 Concluding remarks

This paper deals with the economic value of university education measured in terms of subjective valuations by college students. We used a microeconomic data set previously exploited by Alonso-Borrego et al. (2007) that includes academic, personal and familial characteristics, as well as expected and shadow wages. Since declared wages were discretized into five categories, OLS estimation was inappropriate. However, we used information on wage thresholds to obtain more efficient estimates than those provided by a standard ordered probit model.

Differences in time to completion may affect subjective valuation of studies by students. Such differences may affect individual processing of relevant information. For this reason, we considered two different subsamples, first-year and penultimate-year students.

We found that academic performance was the main determinant of expected wages. There were also differences depending on the student degree year, so that expected wages depended on pre-university academic performance for first-year students and on college performance for later-year students. Comparison of predicted expected wages with actual wages for young working graduates revealed a positive gap on average. This gap tended to narrow for later degree years. This result reflects the fact that expectations became more realistic as students approached graduation.

In relation to shadow wages, the results are consistent with our theoretical framework. In particular, positive academic performance and family background tend to increase shadow wages. The shadow wage predictions obtained from our estimations are also consistent with the theory. In particular, the precision in predicting shadow wages improves for later-year students. Interestingly, women show a steady pattern in the ratio of shadow to expected wages. Therefore, unlike men, their relative shadow wage is very high from

the start of their university degree course.

We used a rich information set that included degree characteristics in terms of discipline and length, which confers robustness to our results.

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Table 1
Monthly expected and shadow wages of Madrid college students
Relative frequency (%)

	Expected	Shadow
Between 450 and 901 euro	4.89	2.07
Between 901 and 1803 euro	17.87	14.51
Between 1803 and 3606 euro	52.66	17.94
Between 3606 and 5409 euro	13.79	28.15
More than 5409 euro	10.80	37.32
Number of observations	1371	1254

Source: Young people towards university, 2001, 2004 and 2005.

Table 2
Main variables and descriptive statistics

	All		Female		Male	
Variable	Mean	S.D.	Mean	S.D.	Mean	S.D.
Female	0.57	0.50				
Family						
High income	0.19	0.39	0.14	0.35	0.26	0.44
University father	0.41	0.49	0.40	0.49	0.42	0.49
Pre-university						
Public secondary	0.58	0.49	0.59	0.49	0.57	0.49
Science secondary	0.52	0.50	0.50	0.50	0.54	0.50
Access grade	67.78	9.32	67.69	9.50	67.90	9.07
Examination passed at first attempt	0.84	0.37	0.87	0.34	0.81	0.40
Choice set						
External choice	0.22	0.42	0.24	0.43	0.21	0.41
Same degree	0.15	0.35	0.15	0.36	0.14	0.35
Same university	0.07	0.26	0.07	0.26	0.06	0.25
University degree chosen						
First choice	0.61	0.49	0.66	0.47	0.54	0.50
Long degree	0.80	0.40	0.79	0.41	0.81	0.39
Science degree	0.46	0.50	0.44	0.50	0.50	0.50
Science long degree	0.34	0.47	0.32	0.46	0.36	0.48
Joint degree	0.01	0.10	0.01	0.08	0.02	0.12
College performance						
Grant	0.17	0.37	0.18	0.39	0.15	0.35
Repeater	0.30	0.46	0.27	0.45	0.35	0.48
Satisfied	0.21	0.41	0.25	0.43	0.16	0.37
Working	0.18	0.39	0.18	0.39	0.18	0.39
Survey year						
2004	0.31	0.46	0.25	0.43	0.40	0.49
2005	0.56	0.50	0.61	0.49	0.50	0.50

Source: Young people towards university, 2001 2004 and 2005.
All the variables are binary except for Access grade, which ranges between 50 and 100.

Table 3
Monthly average earnings by educational level completed
Employees aged 20–29 years

	Secondary	Technical	Short degree	Long degree
National average				
All	1357	1359	1774	1995
Men	1538	1554	1999	2178
Women	1192	1147	1615	1843
Madrid average				
All	1417	1389	1960	2226
Men	1617	1578	2191	2505
Women	1243	1223	1769	2002
Percentage wage gap between Madrid and the national average				
All	4.42	2.18	10.48	11.57
Men	5.14	1.55	9.59	15.01
Women	4.34	6.65	9.57	8.62

Source: Survey of wage structure, 2002 (INE)

Table 4
Monthly average earnings by educational level completed
in Madrid relative (%) to long-degree graduates

	Secondary	Technical	Short degree
Unadjusted			
Men	54.90	58.70	14.33
Women	61.01	63.66	13.16
Adjusted for years spent in higher education			
	Secondary	Technical	Short degree
Men	7.32	10.77	4.75
Women	4.84	9.64	4.84

Source: Survey of wage structure, 2002 (INE) and
our own calculations.

Table 5
Expected wage for first-year college students
Pointwise censored model without selection

Public secondary	−0.0404	−0.0329	
Access grade	−0.0078	−0.0074	−0.0076
Access at first attempt	−0.7658*	−0.7135*	−0.7231*
First attempt × Access grade	0.0114*	0.0108*	0.0107*
External choice	−0.1175*	−0.1175*	−0.1229**
University father	0.1066**	0.1071**	0.1212***
Science secondary	−0.2549***	−0.2606***	−0.2571***
Grant	−0.0696	−0.0703	
First choice	−0.0494	−0.0579	
Same degree	−0.097	−0.1021*	−0.0929
Same university	−0.0391	−0.0308	
Joint degree	0.3128	0.3228	0.3523
Reason: Family tradition	−0.0264		
Reason: Economic independence	0.0695		
Reason: University proximity	0.0115		
Reason: Vocation	−0.0715		
Reason: Parental influence	0.0391		
Reason: Difficulty	−0.1053*	−0.0960*	−0.0799
Science degree	0.1294	0.1219	0.1954*
Long degree	−0.1979	−0.1934	−0.0818
Science long degree	0.2177	0.2391	0.2148*
Female	−0.3301**	−0.3245*	−0.1648*
Repeater	0.1271	0.1263	0.0998*
Satisfied	0.4818**	0.4720**	0.3154***
Working	−0.2304	−0.215	−0.043
High income	−0.4202***	−0.4304***	−0.3335**
Science degree ×Female	0.2356	0.2418	
Science degree × Repeater	−0.1909	−0.1675	
Science degree × Satisfied	−0.6375***	−0.6383***	−0.3911***
Science degree × Work	−0.0074	−0.0085	
Science × High income	0.5913***	0.6156***	0.5239***
Long degree ×Female	0.3066*	0.2927*	0.1297
Long degree ×Repeater	−0.0251	−0.009	
Long degree ×Satisfied	−0.1698	−0.1676	
Long degree ×Work	0.2288	0.2073	
Long degree ×High income	0.5403***	0.5591***	0.4618***
Science long degree ×Female	−0.4067*	−0.4078*	−0.1653
Science long degree ×Repeater	0.212	0.1758	
Science long degree ×Satisfied	0.2783	0.2879	
Science long degree ×Work	0.0687	0.0668	
Science long degree ×High income	−0.4825*	−0.5247**	−0.4227*

Of the 371 observations, 68 were right-censored.
*, ** and *** denote significance at 20, 10 and 5 percent, respectively.

Table 6
Expected wage for penultimate-year college students
Pointwise censored model without selection

Public secondary	−0.0238	−0.0252	
Access grade	−0.0005	−0.0013	
Access at first attempt	−0.1932	−0.262	
First attempt × Access grade	0.002	0.0031	
External choice	0.0509	0.0422	
University father	0.0934*	0.0832*	0.0848*
Science secondary	0.0129	−0.0056	
Grant	−0.0396	−0.0352	
First choice	−0.1054*	−0.0919*	−0.0961*
Same degree	−0.0088	−0.0031	
Same university	0.1173	0.0843	
Reason: Family tradition	−0.0556		
Reason: Economic independence	0.0254		
Reason: University proximity	−0.0444		
Reason: Vocation	−0.0458		
Reason: Parental influence	−0.0527		
Reason: Difficulty	−0.0123		
Science degree	0.1853	0.1997	0.2268*
Long degree	0.3281*	0.2972*	0.4459***
Science long degree	−0.4938*	−0.5035**	−0.5356***
Female	−0.4178**	−0.4554***	−0.2337***
Repeater	0.3260*	0.3496**	0.1221
Satisfied	0.2692	0.2741	0.3118*
Working	0.4596**	0.4516**	0.2992**
High income	0.5094***	0.4874***	0.5395***
Science degree × Female	0.4813**	0.5107**	0.3626***
Science degree × Repeater	−0.2592	−0.306	
Science degree × Satisfied	−0.4393*	−0.4355*	−0.4387*
Science degree × Work	−0.2392	−0.2749	
Science degree × High income	−0.6270***	−0.6174***	−0.6107***
Long degree ×Female	0.2094	0.2591	
Long degree ×Repeater	−0.4782***	−0.4964***	−0.2755**
Long degree ×Satisfied	−0.4429*	−0.4457*	−0.4820**
Long degree ×Work	−0.5164**	−0.5108**	−0.3580**
Long degree ×High income	−0.4686***	−0.4457***	−0.5123***
Science long degree ×Female	−0.1095	−0.1291	
Science long degree ×Repeater	0.8237***	0.8604***	0.5666***
Science long degree ×Satisfied	0.7883***	0.7879***	0.7754***
Science long degree ×Work	0.217	0.2649	
Science long degree ×High income	0.3801*	0.3851*	0.3937*

Of the 279 observations, 15 were right-censored. See notes to Table 5.

Table 7
Monthly average expected wages for college students
in Madrid by degree year

In euro

	Short degree		Long degree	
	First year	Penult. year	First year	Penult. year
Male	3070	2351	3811	2646
	973	654	1202	567
Female	2857	2232	3161	2200
	882	719	1060	671

Percentage difference between average expected wage and Spanish average actual wages for working graduates

	Short degree		Long degree	
	First year	Penult. year	First year	Penult. year
Male	53.6	17.6	75.0	21.5
Female	77.0	38.2	71.5	19.4

Percentage difference between average expected wage and Madrid average actual wages for working graduates

	Short degree		Long degree	
	First year	Penult. year	First year	Penult. year
Male	40.1	7.3	52.1	5.6
Female	61.5	26.2	57.9	9.9

Source: Calculated from "Young people facing university", 2001, 2004 and 2005 and Survey of wage structure.

Table 8
Shadow wage for first-year college students
Pointwise censored model without selection

Public secondary	−0.0369	−0.0389	
Access grade	0.0346***	0.0343***	0.0329***
Access at first attempt	2.1966***	2.1797***	2.1094***
First attempt × Access grade	−0.0334***	−0.0331***	−0.0322***
External choice	0.2713***	0.2691***	0.2494***
University father	0.1470**	0.1481**	0.1550**
Science secondary	−0.3113***	−0.3082***	−0.2846***
Grant	−0.1416*	−0.1484*	−0.1602*
First choice	0.0112	0.0158	
Same degree	−0.2929***	−0.2850***	−0.2851***
Same university	0.1638	0.1602	
Joint degree	2.8507***	2.8588***	2.9169***
Reason: Family tradition	0.3637***	0.3638***	0.3795***
Reason: Economic independence	0.1283*	0.1273*	0.1427*
Reason: University proximity	0.0761	0.0733	
Reason: Vocation	0.1067	0.1116	
Reason: Parental influence	−0.2291***	−0.2314***	−0.2325***
Reason: Difficulty	−0.0237	−0.0163	
Science degree	0.3037	0.1322	0.1778
Long degree	0.063	−0.0903	0.0321
Science long degree	−0.1009	0.0944	0.0941
Female	0.1648	0.0308	0.1361**
Repeater	−0.306	−0.3841***	−0.2610**
Satisfied	0.1841	0.0931	0.1629**
Work	−0.1773	−0.3545**	−0.3633**
High income	0.5755***	0.5357***	0.6799***
Science degree × Female	−0.073	0.0783	
Science degree × Repeater	0.1887	0.2697*	0.2269*
Science degree × Satisfied	−0.1635	−0.0275	
Science degree × Work	0.1735	0.3774**	0.3572**
Science degree × High income	−0.4332*	−0.3831***	−0.4126***
Long degree × Female	−0.0487	0.0935	
Long degree × Repeater	0.105	0.1866	
Long degree satisfied	−0.0086	0.1012	
Long degree work	0.1384	0.3304*	0.3237*
Long degree high income	0.1057	0.1494	
Science × Long degree female	0.1725		
Science long degree repeater	0.0902		
Science long degree satisfied	0.1852		
Science long degree work	0.247		
Science long degree high income	0.0607		
Constant	5.3869***	5.5431***	5.6008***
Year 2004	−0.2412	−0.24	−0.2316
Year 2005	0.6513***	0.6542***	0.6777***

Of the 360 observations, 156 were right-censored. See notes to Table 5.

Table 9
Shadow wage for penultimate-year college students
Pointwise censored model without selection

Public secondary	0.0681	0.0721	
Access grade	0.0176*	0.0176*	0.0179**
Access at first attempt	1.5365**	1.4972**	1.4791**
First attempt × Access grade	−0.0265***	−0.0258***	−0.0251***
External choice	−0.0054	−0.0041	0.0091
University father	0.3693***	0.3733***	0.3876***
Science secondary	0.1640*	0.1817*	0.1724*
Grant	0.0586	0.0607	0.0717
First choice	0.089	0.0918	
Same degree	−0.2344***	−0.2439***	−0.2760***
Same university	0.0183	0.0172	
Reason: Family tradition	0.0198	0.0133	
Reason: Economic independence	−0.085	−0.0767	
Reason: University proximity	−0.1572**	−0.1565**	−0.1776***
Reason: Vocation	0.0735	0.0627	
Reason: Parental influence	−0.0162	−0.0088	
Reason: Difficulty	−0.0374	−0.036	
Science degree	0.3726	0.3888**	0.4692***
Long degree	0.3738*	0.3977**	0.4657***
Science long degree	−0.377	−0.4157***	−0.4259***
Female	−0.1595	−0.1327	−0.0512
Repeater	−0.2618*	−0.4044***	−0.2873***
Satisfied	−0.0834	0.0634	0.0756
Work	−0.0136	−0.1045	−0.0925
High income	0.4231	0.4339*	0.3440***
Science × Female	0.2015	0.1613	
Science × Repeater	0.2744	0.4274***	0.2978*
Science satisfied	0.219	0.0135	
Science × Work	−0.3373	−0.2026	
Science × High income	−0.4724	−0.4964***	−0.4918***
Long degree × Female	0.07	0.0381	
Long degree × Repeater	−0.005	0.155	
Long degree × Satisfied	0.5208**	0.3261*	0.3020*
Long degree × Work	−0.0073	0.0924	
Long degree × High income	−0.0779	−0.1012	
Science × Long-degree female	−0.0822		
Science Long degree × Repeater	0.2071		
Science Long degree × Satisfied	−0.3798		
Science Long degree × Work	0.1642		
Science Long degree × High income	−0.0156		

Of the 256 observations, 98 were right-censored

Table 10
Monthly average shadow wages for college students
in Madrid by degree years

In euro

	Short degree		Long degree	
	First year	Penult. year	First year	Penult. year
Male	3953	4556	5796	5401
	1597	1917	5550	1961
Female	5344	4042	6613	5126
	2524	1875	8555	2325

Percentage difference between average shadow wage and Spanish average actual wages for working graduates

	Short degree		Long degree	
	First year	Penult. year	First year	Penult. year
Male	97.7	127.9	166.1	148.0
Female	231.0	150.3	258.8	178.1

Percentage difference between average shadow wage and Madrid average actual wages for working graduates

	Short degree		Long degree	
	First year	Penult. year	First year	Penult. year
Male	80.4	107.9	131.4	115.6
Female	202.1	128.5	230.3	156.0

Source: Calculated from "Young people facing university", 2001, 2004 and 2005 and Survey of wage structure.

Table 11
Shadow wage relative to expected wage
based on model predictions (%)

	Short degree		Long degree	
	First year	Penult. year	First year	Penult. year
Male				
Weighted mean	128.8	193.7	152.1	204.1
Unweighted mean	135.5	197.3	154.0	206.8
Standard deviation	61.8	73.7	134.6	67.2
Female				
Weighted mean	187.1	181.1	209.2	233.0
Unweighted mean	188.7	179.8	206.0	235.7
Standard deviation	79.1	60.0	167.0	90.7

Table 12
Dropout propensity: Shadow wage lower than expected wage

	Short degree		Long degree	
Degree year	No	Yes	No	Yes
1	67	17	239	51
		(20.2)		(17.6)
2	75	12	166	52
		(13.8)		23.9
3	75	22	206	17
		(22.7)		(7.6)
4			167	8
				(4.6)
5			77	3
				(3.8)

Percentages are in parentheses.

Table 13
Dropout propensity: Shadow wage lower than expected wage
Probit estimation

Public secondary	−0.1115	0.0709	−0.0176
Access grade	−0.0486***	−0.0220	−0.2204***
Examination passed at first attempt	−2.9789***	−0.2450	−17.0646***
Access grade × Pass first attempt	0.0465***	0.0086	0.2699***
External choice	−0.7108***	−0.7584***	−0.1132
University father	−0.2753***	−0.2257	−0.5828*
Science secondary	0.2343*	0.2127	−0.6533**
Grant	0.1137	0.3861*	0.2462
First choice	−0.2512**	0.1489	−1.3666***
Same degree	0.1179	0.3779*	−0.0632
Same university	0.0464	−0.2980	1.2897***
2 years to finish	0.3392**		
3 years to finish	0.7390***		
4 years to finish	0.7776***	−0.1737	
Reason: Family tradition	−0.5536***	−0.6094***	−0.5747*
Reason: Economic independence	−0.0709	0.0797	0.0431
Reason: University proximity	−0.0032	−0.3089*	0.1504
Reason: Vocation	0.0435	−0.0293	−0.1648
Reason: Parental influence	0.2534**	0.3515*	0.8895**
Reason: Difficulty	0.2209*	0.0749	−0.2339
Science degree	−1.3243***	0.8658**	−3.8564***
Long degree	−1.1524***	0.5112	−0.2706
Science long degree	1.6119***		
Female	−0.9715**	0.1766	−1.1201*
Repeater	0.7219*	1.3921***	2.0852***
Satisfied	−0.3552	−1.1188*	−0.8186*
Work	0.9778*	2.8072***	2.5596***
High income	−1.5357***	−12.473	−2.2297***
Science degree×Female	1.7701***	−0.2088	3.5163***
Science degree×Repeater	−0.2198	−1.2349**	−0.1294
Science degree×Satisfied	−0.5087	−0.0925	0.1625
Science degree×Work	−1.3867**	−3.0404***	
Science degree×High income	1.3776**	0.9863	
Long degree×Female	0.9396**	−0.3773	0.1267
Long degree×Repeater	−0.2527	−0.2899	−2.4192***
Long degree×Satisfied	0.4157	1.2169*	
Long degree×Currently working	−0.8376*	−2.5867***	−2.4273***
Long degree×High income	0.2795	−0.7257	
Science long degree×Female	−1.9684***	−0.4973	1.6465*
Science long degree×Repeater	0.1071	0.5425	
Science long degree×Satisfied	0.1876		
Science long degree×Work	0.8735	1.9744*	
Science long degree×High income	−0.8945	0.5748	
No. of observations	889	310	180
log-likelihood	−270.3	−107.6	−31.2
Chi-square	172.7	100.4	96.0
Degrees of freedom	45	41	33

See Notes to Table 5.