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Abstract

We consider the academic performance of Italian university graduates and their labour market position three years after graduation. Our data confirm the common finding that female students outperform male students in academia but are overcome in the labour market. Assuming that academic competition is fair and that individual talent is equally distributed by gender, we suggest that the gender gap evident in degree scores is endogenously due to the greater effort exerted by female students. We find that females face a greater increase in labor market returns from signalling through academic performance. This higher prize explains the greater effort exerted by females and the higher probability of winning the academic competition.

JEL classification: G10; I20; J16

KeyWords: Education; Italy; Gender; Tournaments; Sample selection

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1 Introduction

By estimating the academic performance equation of 26006 Italian students who graduated in 2001, and their occupational status and earnings three years after graduation, we find that the educational and occupational performances of male and female students do differ: girls outperform boys in academic achievement, but male graduates outperform female graduates in labor market outcomes. We know from pre-existing literature that on average female students outperform male students in academic achievements in most OECD countries (OECD, 2004), and that wages for women are lower after controlling for education levels and other factors (Blau & Kahn, 2003) even at the beginning of their careers (Kunze, 2005). Even if female graduates earn less than male graduates, our data show that they face a greater *increase* in the labor market return from educational performance.

A higher return on education for females appears to be the norm in both U. S. and European countries (Murnane, Willett, and Levy (1995); Loury (1997); Card (1999); Dougherty (2005); Trostel, Walker, and Woolley (2002); Psacharopoulos and Patrinos (2004) among others) and it is consistent with alternative explanations such as human capital and sorting[1] models of education.[2] However, while most work on educational returns is concerned with the premia for additional qualifications or for years of schooling, we consider degree score for the educational performance[3] as a proxy for the individual ability in order to minimize potential estimation bias attributable to unobserved heterogeneity (See also Dougherty (2005) and Naylor, Smith, and McKnight (2007)).

We provide additional empirical evidence for the Italian graduates and we refer to the economics of tournaments to interpret the gender gap in academic achievements. In educational tournaments rewards depend on ordinal comparisons of academic scores across all students. Becker and Rosen (1992) emphasize the importance of a student's position in the distribution of academic attainment, and they demonstrate that competition among peers does stimulate students' learning effort provided they are appropriately rewarded for achievement.

Using the terminology of O'Keeffe, Viscusi, and Zeckhauser (1984) and Schotter and Weigelt (1992) tournaments may be either symmetric or asymmetric. Symmetric tournaments occur when agents are homogeneous and are treated equally by the rules of the competition. Asymmetric tournaments may be uneven or unfair. A tournament is uneven when agents have different cost-of-effort functions. A tournament is unfair when agents are identical but the rules favor some of them and discriminate against the others.

In this paper we suggest that the educational tournament is uneven demonstrated by the different values that male and female students assign to the prizes received. In particular, the value of the tournament prize depends on the effect of educational performance on the (marginal) expected return in the labor market and we show that this effect it is greater for females than for males. The equilibrium thus predicts that female students exert more effort than male students in the educational tournament.

In Section 4 we attempt to confirm empirically the assumptions put forward by the simple educational tournament model we consider in Section 2 (Section 3 describes our data). First, we show that, for the most part, the difference in educational performance is explained by the diversity in unobserved characteristics (including effort) between male and female students. Second, we attempt to provide empirical evidence that the amount of effort supplied is in fact the key determinant of the unobserved characteristics, able to explain differences in educational performance. Third, we argue that female students dedicate themselves more seriously to study because they gain a higher marginal return in the labor market from success in educational competition.[4] This finding may be consistent with both human capital and sorting models of education. However, we last test successfully the hypothesis that by means of higher grades female students do signal their ability to potential employers.

2 A simple tournament model for educational performance

In tournaments the outcome depends on comparison of performance across players. In our application, this means that students are ranked according to their educational performances. In a general framework, in order to increase their probability of winning the tournament, players have to exert effort which negatively affects their utility. The equality of marginal benefit and marginal cost determines the optimal level of effort for each player. Accordingly, in an educational tournament, both male and female students maximize a utility function whose arguments are the rewards they receive in response to academic achievement and the disutility of effort.

Consider for the sake of illustration only two students: a female (F) and a male (M) student. The students compete against each other in an educational tournament. The utility function of student i, $i = M, F$, is given by:

$$U_i = K_i g_i(e) - c_i(e_i) \tag{1}$$

where K_i is the value attached by individual i to the (unique, for the sake of simplicity) "prize" received by the tournament "winner". $c_i(e_i)$ is the cost of effort e_i for individual i. The probability of winning depends on the amount of effort each individual exerts as well as on the amount of effort put in by the other individual ($i, j = M, F$, $i \neq j$):

$$\text{Prob}\{i \;\text{ win}\} = g_i(e) = g_i(e_i, e_j) \tag{2}$$

where $e = (e_M, e_F)$ is the vector of the efforts offered by students.[5] We assume that $\frac{\partial g_i}{\partial e_i} > 0$ and $\frac{\partial g_i}{\partial e_j} < 0$ and of course $\sum_i g_i(e) = 1$. When both male and female individuals have the same cost function (which here means that they have the same academic ability) and assign the same value to the prize the educational tournament is *even*:

$$\begin{aligned} c_F &= c_M \\ K_F &= K_M \end{aligned}$$

When the students are treated equally by the rules, the educational tournament is *fair*:

$$g_F(.) = g_M(.)$$

If the tournament is fair and even, the optimal individual strategy will be symmetric and in the equilibrium two identical individuals will exert the same level of effort (Becker and Rosen (1992), p. 112).

However, we assume that the value associated to the prize by the individuals depends on their expected (*marginal*) return in the labor market, and that this return differs according to the gender.[6] In particular we have in mind a situation where:

$$U_i = K_i g(e) - c(e_i) \tag{3}$$

with $K_F > K_M$. This simple setup illustrates a tournament which is actually *uneven* through the prize received by the participants.[7]

Under standard regularity conditions, the Nash equilibrium, $e^* = (e_F^*, e_M^*)$, is such that:

$$K_F > K_M \Longrightarrow e_F^* > e_M^* \tag{4}$$

Hence, a higher prize implies a higher level of effort in the educational tournament. The higher the effort, the higher the probability of winning the competition for grades, if the competition is fair (see equation (2)).

We believe this simple model provides a possible rationale for reconciling the evidence (to be presented in the following Sections) that on average female students outperform male students in academic achievements while women receive, conditional on observable variables, lower wages and face a lower probability of being employed.

Two important assumptions of this work are that the educational tournaments are fair and that male and female students have the same academic ability, i.e. talent. Both assumptions appear realistic. The latter is supported by two meta-analyses conducted by Hyde and Linn (1986) and Hyde, Fennema, and Lamon (1990) who evaluate both verbal abilities and mathematical problem solving. They conclude that there are no cognitive gender differences in verbal ability, and that women simply tend to use a different cognitive process in mathematical problem solving. Moreover, the review of 46 psychological meta-analyses (Hyde, 2005) show much evidence for gender similarities: 78 percent of gender differences are small or close to zero. Thus we can reasonably assume the gender similarities hypothesis, i. e. the equal distribution of general talent between men and women as a group.

Educational tournaments could be unfair because of sex bias in educational assessment and gender stereotyping by examiners.[8] While many studies found no evidence that systematic sex bias affects marking (Newstead and Dennis (1990); Dennis and Newstead (1994); McNabb, Pal, and Sloane (2002)), there is some evidence that male prejudice acts against female students. For instance, Spencer, Steele, and Quinn (1999) suggest that because men are expected to outperform women in standardized tests, women experience a stereotype threat that interferes with test performance. Though, as far as we know, there is little evidence supporting the hypothesis that the bias systematically discriminates against female students, and therefore we assume that educational tournaments are fair.

However, the key assumption of the model is that female graduates face a greater increase in labour market returns from educational performance. We interpret this as coming from a stronger signalling value for females than males. In Section 4, we present evidence to support this interpretation by empirically testing the signalling role of educational performance in explaining the higher return on education for females.

3 Data and summary statistics

Our data come from the Survey on Labor Market Transitions of University Graduates carried out in 2004 by the Italian National Statistical Office. The Survey is the result of interviewing Italians who graduated from university in 2001 three years after graduation. The retrospective information gathered allows us to analyze both academic performance (final degree grades) and initial entry into the labor market. The graduate population of 2001 consisted of 155.664 individuals (67.913 males and 87.751 females). The ISTAT survey was based on a 28% sample of these students and was stratified on the basis of degree course taken and by the sex of the individual student. The response rate was about 67.6%, yielding a data-set containing information on 26.006 graduates. The data contain information on educational curriculum, occupational status and the student's family background and personal characteristics.

In particular, the principal variables contained in the data set can be divided into the following five main groups. (i) *University Career and High School Background*: including, kind of high school attended, high school mark, other education, university, subject, duration, degree score, accommodation, work during university, post graduate studies; (ii) *Work Experience*: including, previous experience, experience in actual work, type of work, net monthly wage; (iii) *Search for Work*: including, kind of work desired, willingness to work abroad, preference over working hours, minimum net monthly wage required; (iv) *Family Information*: including, parents' work, parents' education level, brothers and/or sisters; (v) *Personal Characteristics*: including, date of birth, sex, marital status, children, country of domicile, country of birth, residence.

[Tables 1, 2 and 3 here]

Table 1 shows average degree score by gender and field of study. On average female students obtain higher grades in all the types of courses considered (the only exception being Science). The average difference between the female and male score amounts to more than 2 points and ranges from a minimum of 0.27 for Humanities to a maximum of 3.13 for Economics, Business and Statistics.[9] The average grade difference between male and female students is statistically significant for most of the subjects studied, as indicated by the test in the last column of the table. Indeed Figure 1 shows that the empirical distribution of female educational performance even (first-order) stochastically dominates[10] the empirical distribution for male students.[11] Thus our data appear to reject the observation by Hedges and Nowell (1995) that, while on average female students perform better than males, the scores of the latter exhibit a larger variance and tend to concentrate at the upper end of the distribution.

Table 2 reports average monthly earnings and employment probability three years after graduation by gender and field of study. Monthly earnings in 2004 are in euros and net of taxes and social security contributions. The average earnings are 1128, 1226 and 1017 euros per month for the sample as a whole, for the male and the female sub sample, respectively. The average employment probability three years after graduation is 0.75 and 0.66 for male and female candidates respectively.

Therefore, on average, male graduates earn about 20 percent more than females and are more likely to have a job three years after graduation.

Table 3 reports the probability of being employed as entrepreneurs and managers out of the total of graduates employed according to degree groups and gender. The average probability of being employed in an apical job is about 1.91 percent and 0.7 percent for male and female candidates respectively.

We also estimate gender-specific earnings equations by controlling for self-selection.[12]

We then make use of the standard Blinder (1973) and Oaxaca (1973) decomposition which breaks down the overall mean gender wage gap as an "explained" component (due to differences in the average observable variables) and as an "unexplained" component of the gender wage differential. The decomposition of the gender gap in mean log-earnings[13] (0.09) shows that we can explain from 39 to 45 percent of the total, depending upon whether male or female coefficients are used to evaluate gender differences in characteristics.

Overall, we find higher grades for women in almost all types of courses on the one hand, and lower entry wages for women three years after graduation on the other hand. Moreover, less than half of the average gender wage gap is explained by observed individual characteristics.

We acknowledge that our sample is potentially biased. In fact, our data provide information only on individuals who have obtained a university degree: there is no information on any control group of individuals leaving university before reaching degree level. Therefore, in interpreting the effects of a number of the variables, we should recognize the issue of sample selection. Previous empirical research shows, however, a higher drop out rate for male students with respect to female students (Boero, Laureti, and Naylor (2005); Micali (2000); Arulampalam, Naylor, and Smith (2004)).

Therefore, in case of selection bias, this should mainly act against female students in educational performance achievements.

4 Empirical analysis

In this section we investigate our data. First, we examine whether the difference in the educational performance between men and women survives the inclusion of relevant control variables and the extent to which performance differences by gender can be explained according to gender differences in observed characteristics (Section 4.1). In particular, we attempt to provide empirical evidence that the amount of effort supplied represents a large part of the unobserved characteristics underlying the gender gap in academic achievement (Section 4.2). Moreover, we show that the marginal effect of educational performance on wages is higher for female graduates than for male graduates (Section 4.3). We interpret this as evidence of a stronger signalling effect for females than males, which possibly explains the higher value female students assign to the educational tournament prize. Last, we compare an explanation of gender difference in educational performance based on a signalling effect with the alternative explanation based on human capital investment (Section 4.4).

4.1 Factors affecting the gender difference in educational performance

To measure the impact of gender on educational attainment, we estimate the educational performance equation for female and male graduates. The estimation results are then used to investigate whether the gender effect in terms of degree performance arises because of observed differences between male and female characteristics or because of unobserved input.

Focusing on subsequent job market entry, two dimensions of academic performance are taken into account: degree score and the speed at which students complete their academic career. In order to take into account both dimensions, we build up the following measure for educational performance:

$$edperf = \frac{dscore}{1 + 0.10 \times years} \tag{5}$$

where *dscore* is the degree mark plus the laude or highest honors when it occurs. The degree scores in the publicly available data are provided in brackets rather than as a continuous variables. They fall into four intervals (< 79, 80-89, 90-94, 95-99) and for scores higher than 99 the effective value is disposable. We treat the degree mark as continuous variable by using the midpoint of each range when the value is not available. The number of years in excess (*years*) used to get the degree[14] is eventually corrected for those having carried out military service during their university years. Obviously, the degree scores have been normalized to take into account the different marking scale for each faculty.[15]

In the educational performance equation we consider as explanatory variables both those variables determined prior to the time students enter college and those linked to the kind of degree obtained and determined during the time students attend university. To the first set belong marks gained in the high school graduation exam and dummy variables for the type of high school attended (whether generalist or technical/professional). We include also family background variables such as parental education and occupation, the presence of siblings and the father's activity status when the individual was 14. The second set of variables includes a dummy variable indicating whether the student moved to attend university, dummies for degree subject and the university attended.

[Table 4 here]

Table 4 reports the main results separately for the 8686 female students and 7768 male students.[16]

Last, we decompose the male-female differential in educational performance by means of the the standard Blinder (1973) and Oaxaca (1973) decomposition. We observe that although differences in attributes are important in explaining gender differences in educational attainment, with about 44% of the gender gap in attainment being due to differences between male and female characteristics, differences in the *unobserved* characteristics do also matter. Indeed, about 56% of the gender differences in educational attainment have to do with differences in *unobserved* inputs.[17]

4.2 Accounting for the unobserved characteristics which explain gender difference in educational performance

We claim that a large part of the (unexplained) difference in educational performance between male and female students is given by the difference in the amount of effort the latter choose to devote to their studies. We believe that female students choose intentionally to outperform male students to signal their ability to potential employers (we will take up this point again in Section 4.4 to explain why this is rational for them). To test this hypothesis we compare the educational performance of full-time and part-time students. The latter are severely time constrained, and can exert only a limited control over the amount of effort to devote to academic activity.

[Table 5 here]

Table 5 shows estimates of the educational performance for full-time and part-time students. The equations are very similar in terms of magnitude, sign and statistical significance of the estimated parameters. The only exception is represented by the female dummy (*Female*) which is not statistically significant for students in full time employment.[18] Hence, the evidence of female educational over-performance holds only for full time students and not for students who are also working while they attend university.

This suggests that the gender difference is not relevant *per se* in explaining the educational performance differential (as it should be if it were due to different inherent abilities), and that is endogenously related to the labor market status. Our explanation for this is twofold. First, part-time students find more difficult to engage in signalling activities. Second, students in full-time jobs may have less incentive to signal their ability to future employers because possibly they have already started a career.[19]

4.3 Different values assigned to the prizes received in the educational tournament

One could wonder why female students put more effort into educational performance than male students, given that they will receive lower wages. We find a rationale for this choice in the higher marginal return that female students gain from their higher grades. Even if female graduates earn less than male graduates, our data show that they face a greater increase in the labor market return from educational performance.

To this end, the following earnings equation was estimated for full-time workers:

$$ln(w) = \alpha + \beta_1 edperf + \beta_2^{'}E + \beta_3^{'}X + \beta_4^{'}Z + \epsilon$$

where w is the monthly wage,[20] $edperf$ is educational performance, E is a vector of educational dummy variables, X is a vector of personal characteristics and Z is a vector of regional dummy variables.

Assuming that the self-employed have no need to signal innate ability to a future employer, we estimate the earnings functions for the employees (male and female samples) by controlling for self selection in the employment status (employees versus self-employed).[21] The sample selection model is estimated by means of the Heckman (1979) two-step procedure. Such estimation takes into account the possibility that individuals may select a particular employment status for themselves because they have a comparative advantage.

[Table 6 here]

Table 6 shows the estimation of the wage regression for employees. The results of the first-stage probit model are presented in Table 8. In Table 6 the significance of *lambda* confirms the selectivity bias for both samples. Table 7 shows that the magnitude of the estimated coefficients on educational performance (*edperf*) is always greater for the female sample and that the difference in coefficients between females and males is statistically significant for all specifications, as indicated by the test at the bottom of the table.

4.4 Human capital versus signalling hypothesis

A higher return on education for females is common in literature,[22] and it is consistent with alternative explanations such as human capital and sorting models of education. Empirically, both theories predict the same patterns: females have a greater incentive to exert effort in school because educational performance is worth more (at the margin) in the labour market to females than to males.

To see whether the sorting or the human capital theory supports the higher return on education for females, we test the screening hypothesis. While human capital theory holds that educational performance augments individual productivity, the screening hypothesis attests that educational performance only signals inherent productivity.

Following Brown and Sessions (1998) and Brown and Sessions (1999) we test two versions of the screening hypothesis: the strong screening hypothesis (SSH) and the weak screening hypothesis (WSH). The SSH states that schooling is merely a signal for employers of the productivity of an employee. The WSH on the other hand states that the primary role of schooling is to signal, but that schooling also has some inherent productivity.

We build on the educational screening theory starting with the assumption that screening is more important in some sectors than in others. In particular, we assume that the self-employed constitute the *unscreened control group* because they have no need to signal innate ability to a future employer, and we compare the rates of return to education across this and the employee subsample (*the screened group*). In this framework, the returns to education for the self-employed are nothing but true returns to human capital.

The WSH implies a significant positive return on education for the self-employed, but a significantly higher positive return for employees. The SSH, in contrast, implies an insignificant return on education for the self-employed, but a significantly positive return for employees (Brown and Sessions (1998); Brown and Sessions (1999)).

[Table 7 here]

Tables 6 and 7 show the estimation of the wage regression for employees and the self-employed, respectively. While we observe a positive selection bias for employees, the estimates do not suggest any significant selection bias for the self-employed.[23] The educational performance coefficient (*edperf*) is statistically significant only for employees (both the female and male sample). Hence, our results support the SSH, i. e. that educational performance has an insignificant return for the self-employed, but a significantly positive return for employees.

This finding appears to support our statement that the unobserved input that causes the gender gap is nothing but signalling effort.

[Table 8 here]

5 Conclusions

We consider the academic performance of Italian university students and their labor market position three years after graduation. Our data confirm the well-established stylized fact that female students outperform male students in academia but are overcome in the labor market. By decomposing the gender difference in educational performance between observed and unobserved factors we also find that about 56 percent of it is due to unobserved inputs. Assuming that academic competition is fair and that individual talent is equally distributed by gender, we suggest that the gender gap evident in degree scores is due to the greater individual effort endogenously exerted by female students.

To provide support to our thesis, we first show that the gender difference in educational performance actually vanishes when we consider the time-constrained part-time students, which would not happen if it were based on systematic gender differences in individual ability. Second, we test the hypothesis that the labor market value of academic achievements is greater for female students, and find that actually their wage incremental expected value related to educational performance is higher. Last, we test the screening hypothesis to see whether the higher return on education for females is supported by the signaling or by the human capital theory. We find that the higher return on education for females comes from its signaling value.

These findings suggest a reconciliation of the stylized fact concerning the gender differential in educational performances and market earnings which supports our main thesis and is based on simple results from the economics of tournaments. Since the "prizes" assigned in academic tournaments have a larger (expected) signalling value for female students, those tournament are in fact "uneven" by gender even when "fair" (according to tournament terminology). Thus, female students should be expected to rationally exert more effort than male students, and obviously this implies that indeed in the equilibrium the latter have higher more academic achievements.

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Notes

[1]Following Weiss (1995) we use the term sorting to refer to both signalling and screening of workers; both signalling and screening serve to sort workers according to their unobserved abilities.

[2]As stressed by Naylor et al. (2007) the student who does better at university could be thought of as having acquired more human capital through more productive study. Alternatively, a higher grade score at university could be interpreted as a signal of higher underlying ability.

[3]See Section 4.1

[4]Other researchers have argued that women receive higher grades than men because they work harder at school (Wainer & Steinberg, 1992). In Italy the data carried out by Eurostat and referred to the period from April 2002 to March 2003 shows that the average time spent in school and university activities is the same for males and females (Hours 0:04), but the average time spent on homework is higher for females (0:09) than for males (0:06). (Cfr. Harmonised European Time Use Survey 2005-2007 by Statistics Finland and Statistics Sweden. https://www.testh2.scb.se/tus/tus/)

[5]Equation (2) is a reduced form for the stochastic mechanism which assigns the prize as a function of the individual efforts. For example, the effort e_i may affect the distribution $F_i(S_i; e_i)$ of the academic achievements S_i of individual i while the prize is ex post assigned to the individual associated with the best achievements.

[6]In the empirical analysis of Sections 3 and 4, we show that while women earn less (after controlling for education and other factors) even at the beginning of their career, female graduates face an higher marginal effect of educational performance on their wages with respect to male graduates.

[7]This model is equivalent to a tournament where the value of the prize is normalized to one for everybody but the cost function differs among individuals. The strategically equivalent utility function for individual i may be written as: $\widetilde{U}_i = g(e) - \frac{c(e_i)}{K_i}$.

[8]Sex bias can occur when there are differences in the way male and female

students respond to different types of assessment. Gender stereotyping can occur when the score given by an examiner is affected by favouritism towards students of one sex.

[9]The final degree score ranges from 66 to 110 (for some Universities the maximum mark awarded is 100). According to each faculty internal ruling a laude (distinction) may be assigned to candidates with a 110/110 mark for recognition of the excellence of their thesis (in this analysis the 110 *cum laude* was transformed to 113).

[10]First-order stochastic dominance is a possible ordering between two stochastic distributions. Let $F(x)$ and $M(x)$ denote the cumulative distribution functions of the educational performance x for female and male students, respectively. F first-order stochastically dominates M if and only if for every possible educational performance x, $F(x) \leq M(x)$. This means that for every possible value of x, the probability of getting a educational performance that high is never better in M than in F.

[11]Figure 1 shows the cumulative distribution functions of educational performance for female and male students. We only present results for the whole sample but we also find very similar results when we consider specific degree subjects. The only exception is represented by Science where the two cumulative distribution functions cross several times but are very close throughout the entire range of educational performance.

[12]The results of these estimations are not reported but are available on request from the authors. The dependent variable is the natural logarithm of the net monthly wage. We control for all the variables included in table 6.

[13]The gender wage gap is quite significant given the fact that we are considering a sort of first-job market entry.

[14]In the Italian education system, each faculty only sets a minimum num-

ber of years in which to obtain a degree. As a consequence there is a high dispersion in the age at which students graduate. The speed of completion of the academic career is, therefore, together with the final mark, an important component of educational performance.

[15]See footnote 9.

[16]From here on, we omit students who graduated in the field of medicine from the empirical analysis as the career path for these students is very different from that of other students. After having obtained their degree in medicine, in general the students carry out a specialist activity which lasts at least three additional years.

[17]In a preliminary version of this paper, we estimated the educational performance equations by means of separate ordered probit for female and male graduates in line with the analysis of McNabb et al. (2002). The Jones and Makepeace (1996) decomposition approach showed that about 36% of the gender differences in educational performance is explained by the difference in observed characteristics between male and female students, leaving about 64 percent due to unobserved inputs.

[18]As in the Italian university system course attendance is not compulsory but discretionary, the student population may be disaggregated as follows: studying-workers (they have a full time job while studying at university and amount to 14 percent of the student population); working-students (they have a part time job while studying at university and amount to 47 percent of the student population); studying-students (they only study and do not work before completing their degree and amount to 38 percent of the student population). This distribution is the same for both male and female students.

[19] Alternative interpretations are of course possible. For example, female students may surpass male students in educational performance because are

characterized by a greater sense of duty or self-discipline (Duckworth & Seligman, 2006), significantly affecting the results only when there is enough time to divide between study and leisure. We test these two alternative explanations checking whether educational performance exhibits some gender bias when the sample is restricted to full-time students that are self employed at the time of the survey. Indeed, also in this case there should be a weak incentive to engage in signalling (both for men and women), while it is at best unclear why the female sense of duty should not be at work. The result confirms our guess: the female dummy is not statistically significant.

[20]The monthly wages are in euros and net of taxes and social security contributions.

[21]The choice of whether or not to be self-employed is clearly endogenous. Some individuals will have unmeasured traits that make it more likely that they will excel as entrepreneurs, while others have traits that will make them better suited to dependent employment. As a consequence, the observed differences in returns to education may not accurately reflect what would happen if the same group of workers were simultaneously observed as self-employed or employees.

[22]Previous findings reveal that a higher return on female education appears to be the norm in both U. S. and European countries (Murnane et al. (1995); Loury (1997); Card (1999)). Dougherty (2005) summarizes 27 U. S. studies focusing on the returns on education with data on both sexes. Of the 27 studies, 18 report unambiguously higher coefficients for females. Six report multiple estimates where the female coefficients are mostly higher. Two report mixed results that are evenly balanced. Trostel et al. (2002) estimate the returns on education in 28, mostly European, countries and found that the female education coefficient was higher in 24. Psacharopoulos and Patrinos (2004) list 95 estimates of male and female education coefficients from 49

countries at different dates. Of these 63 are greater for females, three are equal, and 23 are greater for males (Naylor et al., 2007).

[23]Rees and Shah (1986), Brown and Sessions (1999) and Johansson (2000), among others, find the same result.

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Figure 1
Average grade by gender and field of study

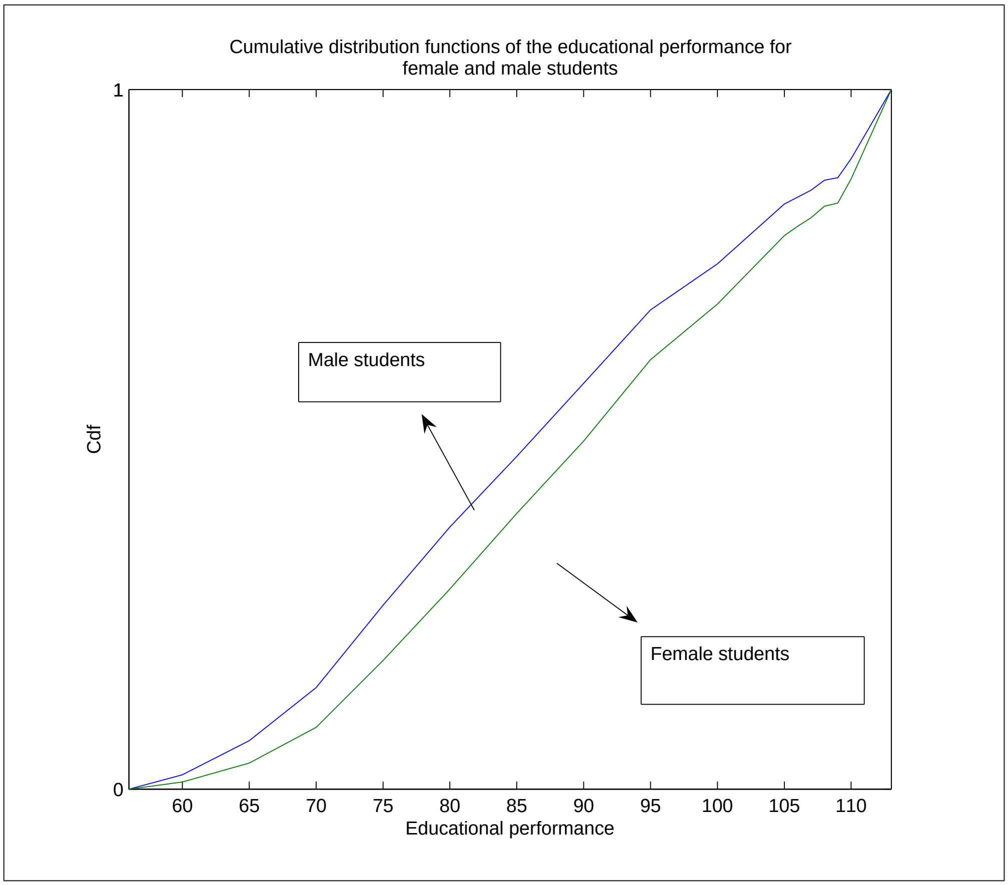

Table 1
Average grade by gender and field of study

Field of study	Male students	Female students	T-statistic
Sciences	102.80	102.06	-1.60
Pharmacy	101.12	102.58	3.12
Natural sciences	104.29	105.66	3.73
Medicine	105.46	107.00	8.99
Engineering	100.95	103.39	6.95
Architecture	103.43	104.47	2.78
Agricultural studies	103.26	104.74	3.44
Economics, business and statistics	98.12	101.26	11.11
Political science and sociology	100.94	102.71	4.11
Law	96.16	98.99	7.64
Humanities	106.98	107.25	1.08
Foreign languages	105.12	105.60	0.96
Teachers college	105.96	106.29	0.78
Psychology	101.40	104.09	4.94
Health	107.57	107.96	1.21
Total	101.95	104.01	21.21

Table 1 reports average grade by gender and field of study. The university mark, in the Italian System, ranges from 66 to 110, eventually plus *laude*, denoting excellence. The last column reports the values of the T-statistic for the Null Hypothesis that the difference between the average grades is zero.

Table 2
Average earnings and employment probability by gender and field of study

	Average monthly earning		Average monthly probability	
Field of study	Male	Female	Male	Female
Sciences	1220.43	1003.87	0.71	0.68
Pharmacy	1292.83	1089.34	0.84	0.77
Natural sciences	1074.25	1034.81	0.74	0.62
Medicine	1336.08	1097.90	0.41	0.30
Engineering	1318.57	1200.84	0.90	0.85
Architecture	1140.36	918.41	0.88	0.82
Agricultural studies	1087.28	921.93	0.81	0.69
Economics, business and statistics	1251.43	1104.73	0.82	0.77
Political science and sociology	1235.09	1056.38	0.86	0.85
Law	1080.43	895.73	0.62	0.52
Humanities	961.86	901.19	0.70	0.71
Foreign languages	1117.55	973.30	0.79	0.78
Teachers college	1078.29	948.69	0.86	0.84
Psychology	997.19	896.19	0.81	0.74
Health	1206.88	973.42	0.90	0.89
Total	1225.88	1017.38	0.75	0.66

Table 3
Probability of being employed in entrepreneurial and managerial positions three years after graduation by gender and field of study

	Male students	Female students
Sciences	0.93%	0.35%
Pharmacy	1.07%	0.39%
Natural sciences	1.01%	0.50%
Medicine	2.22%	1.11%
Engineering	2.23%	0.13%
Architecture	1.45%	0.52%
Agricultural studies	3.58%	1.43%
Economics, business and statistics	2.85%	0.54%
Political science and sociology	3.03%	0.92%
Law	1.33%	1.02%
Humanities	1.18%	1.37%
Foreign languages	0.30%	2.25%
Teachers college	1.07%	0.81%
Psychology	1.40%	0.23%
Health	1.67%	0.56%
Total	1.91%	0.70%

Table 4
OLS estimation results of the educational performance equation for male and female students

Variable	Female Students		Male Students	
	Coefficient	T-ratio	Coefficient	T-ratio
Constant	69.695	41.979	68.208	37.062
High School Mark	0.638	33.837	0.674	33.401
Subject (omitted group = Health)				
Sciences	-25.228	-22.259	-22.284	-18.100
Pharmacy	-17.860	-16.608	-17.568	-13.918
Natural sciences	-15.189	-14.250	-14.605	-11.595
Engineering	-23.293	-20.817	-25.607	-22.262
Architecture	-23.138	-19.409	-19.977	-15.724
Agricultural studies	-11.997	-9.872	-14.480	-11.050
Economics, Business and Statistics	-23.989	-23.758	-24.366	-21.190
Political Science and Sociology	-16.919	-16.391	-17.511	-14.493
Law	-26.581	-26.085	-26.260	-21.984
Humanities	-17.366	-17.073	-15.287	-12.249
Foreign languages	-20.712	-19.648	-15.225	-7.443
Teachers college	-11.951	-11.360	-11.182	-5.852
Psychology	-12.913	-11.416	-14.703	-10.320
School type (omitted group = professional school)				
Liceo	5.599	7.818	5.213	5.984
Arts	-0.755	-0.695	-1.493	-0.964
Magistrale	0.778	0.992	1.815	1.063
Technical institute	2.218	3.019	2.426	2.800
Father's degree				
University	0.533	1.105	-0.005	-0.009
High School	0.600	1.742	-0.348	-0.916
Mother's degree				
University	2.338	4.022	2.925	4.784
High School	1.187	3.396	1.023	2.686
Father Occupational status	1.061	1.752	-0.583	-0.874
Father's occupation				
Manager	-0.196	-0.401	-0.016	-0.031
Executive cadre	-0.214	-0.436	0.664	1.325
White collar	-0.600	-1.639	0.107	0.273
Mother's occupation				
Manager	1.575	1.120	0.928	0.586
Executive cadre	0.240	0.418	-1.221	-2.008
White collar	0.877	2.314	-1.162	-2.826
Not born in Italy	0.008	0.004	-8.587	-3.240
Previously attended a different degree course	0.095	0.231	0.096	0.225
Studied in the same town of residence	0.639	2.256	0.761	2.489
Moved to a different town to attend university	-1.378	-3.996	-0.794	-2.139
Frequency of private courses during university	-4.472	-5.939	-3.954	-4.755
Siblings	-0.913	-2.648	-0.337	-0.900
Course attendance	5.294	17.673	5.746	18.418
Possession of other degree	2.586	4.284	5.461	7.953
College dummies	X		X	
Number of observations	8686		7768	
Rbar-squared	0.35		0.34	
F	51.005 (0.00)		42.615 (0.00)	

P-values are represented in parenthesis.

Table 5
OLS estimation results of the educational performance equation: full-time and part-time students

	Working during University		Not working during University	
Variable	Coefficient	T-ratio	Coefficient	T-ratio
Constant	79.491	32.205	61.198	19.242
High School Mark	0.429	13.386	0.752	30.209
Female	0.513	1.028	1.159	3.168
Subject (omitted group = Health)				
Sciences	-28.332	-18.480	-20.735	-7.940
Pharmacy	-23.058	-13.673	-15.463	-5.963
Natural sciences	-18.727	-11.713	-13.432	-5.173
Engineering	-25.336	-19.126	-23.678	-9.205
Architecture	-22.895	-13.103	-19.727	-7.395
Agricultural studies	-17.702	-8.348	-11.567	-4.299
Economics, Business and Statistics	-26.475	-22.224	-21.253	-8.304
Political Science and Sociology	-18.492	-15.715	-15.836	-5.989
Law	-27.688	-22.131	-24.741	-9.663
Humanities	-17.717	-14.683	-15.760	-6.066
Foreign languages	-23.193	-15.537	-18.518	-6.845
Teachers college	-16.563	-13.066	-9.524	-3.422
Psychology	-17.062	-10.829	-10.822	-4.019
School type (omitted group = professional school)				
Liceo	4.624	4.028	5.323	4.592
Arts	-4.044	-1.869	-0.818	-0.430
Magistrale	1.790	1.446	-1.317	-0.942
Technical institute	2.096	1.838	2.032	1.727
Father's degree				
University	-0.605	-0.677	0.924	1.491
High School	-0.242	-0.401	1.224	2.603
Mother's degree				
University	2.657	2.413	2.537	3.602
High School	0.813	1.291	1.094	2.341
Father Occupational status	0.139	0.138	0.892	1.035
Father's occupation				
Manager	0.188	0.208	-0.325	-0.544
Executive cadre	-0.139	-0.156	-0.099	-0.169
White collar	0.615	0.959	-0.951	-1.989
Mother's occupation				
Manager	6.064	2.063	-1.455	-0.857
Executive cadre	-0.144	-0.131	-0.832	-1.239
White collar	0.065	0.092	-0.965	-2.011
Previously attended a different degree course	0.335	0.599	0.021	0.035
Studied in the same town of residence	0.088	0.178	1.389	3.730
Moved to a different town to attend university	-0.817	-1.338	-1.963	-4.363
Frequency of private courses during university	-3.434	-2.860	-2.834	-2.735
Course attendance	5.227	10.638	5.123	11.823
Possession of other degree	4.289	6.431	3.488	3.094
Siblings	-0.040	-0.063	0.133	0.305
Not born in Italy	1.487	0.366	-4.245	-1.150
College dummies	X		X	
Number of observations	2814		5197	
Rbar-squared	0.47		0.34	
F	27.147 (0.00)		29.177 (0.00)	

P-values are represented in parenthesis.

Table 6
OLS estimation results of the earnings equation for the employees (male and female samples)

	Specification 1		Specification 2		Specification 3	
	female	male	female	male	female	male
Variable	Coefficient	Coefficient	Coefficient	Coefficient	Coefficient	Coefficient
Constant	2.914 (124.302)	3.038 (94.895)	2.934 (137.912)	3.042 (102.257)	2.885 (115.053)	3.053 (96.972)
Lambda	-0.077 (-1.895)	-0.119 (-3.216)	-0.056 (-1.705)	-0.093 (-2.723)	-0.030 (-1.145)	-0.068 (-2.310)
Edperf	**0.00093 (7.542)**	**0.00039 (2.864)**	**0.00090 (7.902)**	**0.00044 (3.353)**	**0.00094 (8.261)**	**0.00039 (3.023)**
Experience	0.008 (1.907)	0.013 (3.080)	0.006 (1.608)	0.013 (3.166)	0.004 (1.145)	0.013 (3.224)
$Experience^2$	0.000 (-0.574)	-0.001 (-1.791)	0.000 (-0.561)	-0.001 (-1.872)	0.000 (-0.191)	-0.001 (-1.863)
Subject (omitted group = Health)						
Sciences	0.033 (1.795)	-0.019 (-0.809)	0.040 (2.319)	-0.012 (-0.523)	0.053 (2.773)	-0.023 (-0.922)
Pharmacy	0.052 (2.964)	0.025 (1.155)	0.060 (3.633)	0.032 (1.498)	0.074 (3.967)	0.022 (0.921)
Natural sciences	0.042 (2.690)	0.024 (1.154)	0.045 (2.900)	0.024 (1.146)	0.055 (2.948)	0.005 (0.207)
Engineering	0.094 (6.117)	0.034 (1.684)	0.094 (6.254)	0.035 (1.765)	0.105 (5.616)	0.018 (0.797)
Architecture	0.072 (2.384)	0.071 (2.273)	0.057 (2.230)	0.054 (1.780)	0.055 (1.957)	0.023 (0.667)
Agricultural studies	0.003 (0.172)	0.017 (0.808)	0.000 (-0.004)	0.009 (0.450)	0.006 (0.308)	-0.014 (-0.559)
Economics, Business and Statistics	0.043 (2.606)	0.007 (0.347)	0.047 (3.020)	0.007 (0.373)	0.062 (3.418)	-0.011 (-0.463)
Political Science and Sociology	0.015 (0.900)	0.001 (0.059)	0.017 (1.111)	0.000 (0.011)	0.033 (1.796)	-0.009 (-0.372)
Law	0.048 (2.743)	0.047 (2.039)	0.044 (2.673)	0.038 (1.679)	0.054 (2.739)	0.015 (0.571)
Humanities	-0.011 (-0.689)	-0.050 (-2.230)	-0.005 (-0.336)	-0.048 (-2.218)	0.008 (0.433)	-0.061 (-2.428)
Foreign languages	-0.011 (-0.644)	-0.018 (-0.775)	-0.008 (-0.513)	-0.020 (-0.873)	0.015 (0.796)	-0.038 (-1.475)
Teachers college	-0.033 (-1.957)	-0.047 (-1.947)	-0.029 (-1.789)	-0.050 (-2.095)	-0.011 (-0.588)	-0.065 (-2.432)
Psychology	-0.022 (-1.084)	-0.035 (-1.425)	-0.028 (-1.393)	-0.037 (-1.488)	-0.017 (-0.751)	-0.060 (-2.149)
School type (omitted group = professional school)						
Liceo	0.018 (2.030)	0.021 (2.030)	0.015 (1.767)	0.017 (1.735)	0.012 (1.409)	0.013 (1.321)
Arts	0.011 (0.735)	0.041 (1.547)	0.006 (0.397)	0.035 (1.358)	0.010 (0.685)	0.031 (1.196)
Magistrale	0.016 (1.596)	0.017 (0.724)	0.019 (1.966)	0.018 (0.776)	0.021 (2.170)	0.018 (0.780)
Technical institute	0.008 (0.954)	0.014 (1.379)	0.008 (0.882)	0.011 (1.130)	0.007 (0.837)	0.009 (0.869)
Previously attended a different degree course	0.007 (1.310)	0.014 (2.294)	0.006 (1.270)	0.013 (2.193)	0.008 (1.609)	0.012 (1.943)
Studied in the same town of residence	-0.001 (-0.237)	-0.004 (-0.917)	0.002 (0.429)	-0.002 (-0.467)	0.003 (0.937)	0.000 (0.069)
Moved to a different town to attend university	0.011 (2.672)	0.012 (2.793)	0.010 (2.592)	0.012 (2.913)	0.013 (3.023)	0.010 (2.239)
Married	0.001 (0.220)	0.011 (2.744)	0.001 (0.346)	0.011 (2.794)	0.003 (0.784)	0.010 (2.531)
Region dummies			X	X	X	X
College dummies					X	X
Number of observations	3324	4006	3324	4006	3324	4006
Rbar-squared	0.15	0.07	0.18	0.9	0.20	0.11
F	23.509 (0.00)	13.266 (0.00)	19.157 (0.00)	11.152 (0.00)	9.08 (0.00)	5.53 (0.00)
F test for the equality of parameters	13.142 (0.00)		9.168 (0.00)		4.266 (0.00)	

Table 6 reports the estimates of the earnings equation for employees. T-statistics for parameter estimates and p-value for tests appear in parentheses.

Table 7
OLS estimation results of the earnings equation for the self-employed (male and female samples)

	Specification 1		Specification 2		Specification 3	
	female	male	female	male	female	male
Variable	Coefficient	Coefficient	Coefficient	Coefficient	Coefficient	Coefficient
Constant	2.748 (13.560)	2.896 (20.084)	2.783 (10.973)	2.703 (15.086)	2.800 (9.465)	2.724 (13.619)
Lambda	0.070 (0.632)	0.118 (1.370)	0.005 (0.037)	0.117 (1.329)	0.003 (0.024)	0.085 (0.975)
Edperf	**0.00079 (1.084)**	**0.00007 (0.116)**	**0.00100 (1.249)**	**-0.00016 (-0.258)**	**0.00093 (1.169)**	**0.00005 (0.072)**
Experience	-0.024 (-0.968)	0.026 (1.624)	-0.043 (-1.672)	0.022 (1.376)	-0.048 (-1.860)	0.018 (1.101
$Experience^2$	0.004 (1.387)	-0.002 (-1.100)	0.005 (1.840)	-0.002 (-0.913)	0.006 (2.064)	-0.001 (-0.639
Subject (omitted group = Health)						
Sciences	0.033 (1.795)	-0.019 (-0.809)	0.040 (2.319)	-0.012 (-0.523)	0.053 (2.773)	-0.023 (-0.922)
Sciences	-0.084 (-0.566)	-0.163 (-1.339)	0.165 (0.970)	-0.018 (-0.133)	0.156 (0.905)	0.013 (0.095)
Pharmacy	0.096 (0.766)	-0.130 (-1.403)	0.330 (2.173)	0.020 (0.180)	0.330 (2.118)	0.044 (0.392)
Natural sciences	0.028 (0.325)	-0.176 (-2.222)	0.228 (1.973)	-0.049 (-0.463)	0.220 (1.871)	-0.041 (-0.389)
Engineering	0.107 (1.320)	-0.101 (-1.317)	0.295 (2.563)	0.027 (0.270)	0.291 (2.458)	0.040 (0.396)
Architecture	0.059 (0.510)	-0.049 (-0.500)	0.178 (1.145)	0.077 (0.583)	0.175 (1.119)	0.051 (0.380)
Agricultural studies	-0.001 (-0.018)	-0.104 (-1.295)	0.195 (1.675)	0.048 (0.438)	0.194 (1.640)	0.040 (0.365)
Economics, Business and Statistics	0.046 (0.432)	-0.132 (-1.661)	0.290 (2.155)	0.001 (0.010)	0.291 (2.143)	0.017 (0.166)
Political Science and Sociology	-0.004 (-0.038)	-0.120 (-1.436)	0.233 (1.778)	0.017 (0.161)	0.226 (1.697)	0.021 (0.195)
Law	-0.022 (-0.250)	-0.116 (-1.363)	0.164 (1.322)	0.032 (0.276)	0.155 (1.229)	0.022 (0.189)
Humanities	-0.069 (-0.693)	-0.207 (-2.341)	0.172 (1.333)	-0.067 (-0.612)	0.149 (1.122)	-0.047 (-0.425)
Foreign languages	0.155 (1.385)	-0.159 (-1.653)	0.415 (3.131)	-0.043 (-0.363)	0.415 (3.092)	-0.021 (-0.173)
Teachers college	-0.010 (-0.085)	-0.094 (-0.928)	0.239 (1.658)	0.017 (0.137)	0.243 (1.679)	0.021 (0.172)
Psychology	0.172 (1.794)	-0.041 (-0.459)	0.360 (2.809)	0.085 (0.723)	0.318 (2.301)	0.083 (0.697)
School type (omitted group = professional school)						
Liceo	0.113 (1.649)	0.106 (2.068)	0.023 (0.302)	0.108 (2.098)	0.034 (0.452)	0.104 (2.012)
Arts	0.115 (1.495)	0.172 (2.460)	0.024 (0.288)	0.190 (2.688)	0.053 (0.636)	0.182 (2.562)
Magistrale	0.129 (1.721)	-0.100 (-0.790)	0.090 (1.083)	-0.090 (-0.695)	0.106 (1.260)	-0.071 (-0.547)
Technical institute	0.120 (1.750)	0.095 (1.848)	0.030 (0.399)	0.099 (1.915)	0.047 (0.616)	0.099 (1.908)
Previously attended a different degree course	0.034 (1.142)	0.012 (0.477)	0.018 (0.547)	0.010 (0.385)	0.012 (0.371)	0.001 (0.028
Studied in the same town of residence	0.002 (0.071)	-0.007 (-0.389)	0.017 (0.584)	-0.010 (-0.589)	0.016 (0.525)	-0.010 (-0.594
Moved to a different town to attend university	0.021 (1.012)	0.011 (0.639)	-0.002 (-0.070)	0.008 (0.498)	0.007 (0.273)	0.004 (0.210
Married	-0.026 (-0.992)	0.009 (0.561)	-0.021 (-0.683)	0.009 (0.574)	-0.025 (-0.831)	0.008 (0.469)
Region dummies			X	X	X	X
College dummies					X	X
Number of observations	486	924	486	924	486	924
Rbar-squared	0.12	0.05	0.14	0.06	0.15	0.07
F	3.558 (0.00)	2.509 (0.00)	1.948 (0.00)	1.734 (0.00)	1.807 (0.00)	1.722 (0.00)

Table 7 reports the estimates of the earnings equation for self-employed. T-statistics for parameter estimates and p-value for tests appear in parentheses.

Table 8

First stage probit regressions for the Employment/Self Employment decision underlying Tables 6 and 7. (1=Employed, 0=Self Employed)

	Specification 1		Specification 2		Specification 3	
	female	male	female	male	female	male
Variable	Coefficient	Coefficient	Coefficient	Coefficient	Coefficient	Coefficient
Constant	0.965 (2.300)	0.243 (0.650)	1.348 (3.110)	0.453 (1.190)	1.824 (3.190)	0.888 (1.890)
Edperf	0.006 (2.550)	0.006 (3.730)	0.005 (2.120)	0.006 (3.590)	0.005 (2.200)	0.006 (3.480)
Experience	-0.184 (-2.510)	0.024 (0.410)	-0.206 (-2.740)	0.011 (0.190)	-0.169 (-2.190)	0.029 (0.490)
$Experience^2$	0.019 (2.280)	-0.001 (-0.080)	0.020 (2.320)	0.000 (-0.060)	0.017 (1.950)	-0.002 (-0.290)
Sciences	0.955 (2.910)	1.135 (3.690)	0.953 (2.850)	1.120 (3.610)	0.714 (1.660)	0.941 (2.510)
Pharmacy	0.803 (2.680)	0.755 (2.600)	0.837 (2.730)	0.803 (2.740)	0.658 (1.620)	0.639 (1.780)
Natural sciences	-0.010 (-0.030)	0.033 (0.110)	-0.026 (-0.090)	0.084 (0.290)	-0.263 (-0.660)	-0.097 (-0.270)
Engineering	-0.012 (-0.040)	0.389 (1.410)	-0.023 (-0.080)	0.416 (1.500)	-0.311 (-0.780)	0.179 (0.510)
Architecture	-1.215 (-4.160)	-1.026 (-3.600)	-1.227 (-4.120)	-1.063 (-3.710)	-1.551 (-3.750)	-1.372 (-3.800)
Agricultural studies	-0.302 (-1.020)	-0.322 (-1.130)	-0.290 (-0.960)	-0.280 (-0.980)	-0.551 (-1.370)	-0.509 (-1.430)
Economics, Business and Statistics	0.572 (2.020)	0.478 (1.720)	0.573 (1.990)	0.476 (1.700)	0.370 (0.930)	0.273 (0.780)
Political Science and Sociology	0.377 (1.280)	0.347 (1.190)	0.366 (1.220)	0.357 (1.210)	0.200 (0.490)	0.178 (0.490)
Law	-0.555 (-1.950)	-0.508 (-1.780)	-0.589 (-2.030)	-0.491 (-1.710)	-0.812 (-2.050)	-0.746 (-2.100)
Humanities	0.352 (1.180)	0.280 (0.900)	0.377 (1.240)	0.235 (0.750)	0.090 (0.220)	0.052 (0.140)
Foreign languages	0.626 (2.070)	0.316 (0.950)	0.606 (1.970)	0.274 (0.820)	0.314 (0.770)	0.102 (0.260)
Teachers college	0.487 (1.580)	0.207 (0.610)	0.497 (1.580)	0.181 (0.530)	0.288 (0.700)	-0.030 (-0.080)
Psychology	-0.357 (-1.040)	-0.099 (-0.300)	-0.440 (-1.260)	-0.196 (-0.590)	-0.671 (-1.510)	-0.426 (-1.080)
School type (omitted group = professional school)						
Liceo	-0.287 (-1.470)	-0.325 (-2.170)	-0.285 (-1.430)	-0.289 (-1.910)	-0.240 (-1.180)	-0.312 (-2.040)
Arts	-0.098 (-0.370)	-0.398 (-1.400)	-0.146 (-0.550)	-0.346 (-1.210)	-0.145 (-0.530)	-0.369 (-1.280)
Magistrale	-0.076 (-0.340)	0.114 (0.300)	-0.044 (-0.190)	0.169 (0.440)	-0.042 (-0.180)	0.089 (0.220)
Technical institute	-0.138 (-0.690)	-0.321 (-2.140)	-0.131 (-0.640)	-0.264 (-1.740)	-0.114 (-0.540)	-0.298 (-1.940)
Previously attended a different degree course	-0.083 (-0.830)	-0.204 (-2.700)	-0.054 (-0.530)	-0.188 (-2.460)	-0.092 (-0.870)	-0.227 (-2.910)
Studied in the same town of residence	0.212 (3.280)	0.161 (3.300)	0.209 (3.140)	0.154 (3.060)	0.225 (3.240)	0.143 (2.720)
Moved to a different town to attend university	-0.044 (-0.600)	-0.067 (-1.170)	-0.064 (-0.840)	-0.056 (-0.940)	-0.023 (-0.260)	0.048 (0.710)
Married	0.135 (1.660)	-0.074 (-1.350)	0.159 (1.930)	-0.038 (-0.690)	0.152 (1.770)	-0.045 (-0.790)
Siblings	0.106 (0.230)	-0.552 (-1.280)	0.071 (0.160)	-0.471 (-1.080)	0.238 (0.510)	-0.287 (-0.600)
Father's Degree	-0.009 (-0.150)	0.155 (3.280)	-0.037 (-0.620)	0.144 (3.020)	-0.023 (-0.380)	0.154 (3.160)
Possession of other degree	-0.423 (-1.020)	0.518 (1.360)	-0.399 (-0.970)	0.456 (1.170)	-0.594 (-1.430)	0.280 (0.640)
Father self-employed	0.114 (1.170)	0.153 (2.150)	0.126 (1.270)	0.161 (2.240)	0.115 (1.120)	0.170 (2.300)
Working during University	0.168 (2.720)	0.080 (1.670)	0.139 (2.190)	0.056 (1.140)	0.148 (2.250)	0.065 (1.290)
Region dummies			X	X	X	X
College dummies					X	X
Number of observations	3810	4930	3810	4930	3810	4930
Percent Correctly Predicted:	87.98	82.86	87.98	82.86	88.58	83.41
McFadden's pseudo R-square	0.18	0.13	0.2	0.13	0.22	0.17

Table 8 reports the estimates of the probit regression of the first stage Employment/Self Employment decision underlying Tables 6 and 7. T-statistics for parameter estimates and p-value for tests appear in parentheses.