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THE GENDER GAP IN ACADEMIC ACHIEVEMENTS OF ITALIAN GRADUATES

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ABSTRACT

We analyse the academic performance of Italian students who graduated in 2004, and their occupational status and earnings in 2007. 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 labour market outcomes. 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.

We address our empirical analysis to four points: first, we show that, for the most part, the difference in educational performance is explained by the diversity in unobserved characteristics between male and female students. Second, we provide empirical evidence that the amount of effort supplied is the key determinant of the unobserved characteristics. Third, we argue that female students study hardly because they gain a higher marginal return from success in educational competition. Fourth, as this finding may be consistent with both human capital and sorting models of education, we test the hypothesis that female students use their higher grades to signal their ability to potential employers.

1. INTRODUCTION

The current research literature on the education of male and female students shows that gender patterns of academic achievements change over time and differ between countries. In the past, men typically had better access to university-level institutions: International comparisons establish that in 1990 men still had higher university-level graduation rates than women in half the OECD countries, but the most recent trends in educational participation and performance suggest a world-wide change in academic outcomes between the genders (OECD 2004). Nowadays, female graduates exceed the number of male graduates and on

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average female students outperform male students in academic achievements in most OECD countries (OECD 2009).

Even if educational attainment has an important impact on labor market outcomes, the gender gap in educational performance has received relatively little attention in the economics of education literature (recent examples are, among others, Smith and Naylor 2001, Hoskins, Newstead and Dennis 1997, Naylor and Smith 2004, Naylor, Smith and McKnight 2007, McNabb, Pal and Sloane 2002, Castagnetti, Chelli, and Rosti 2005, Castagnetti and Rosti 2009).

We analyse the academic performance of 26,570 Italian students who graduated in 2004, and their occupational status and earnings 3 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 2009), and that wages for women are lower after controlling for education levels and other factors (Blau and 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 get 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 (Card, 1999; Dougherty, 2005; Loury, 1997; Murnane, Willett and Levy, 1995; Psacharopoulos and Patrinos, 2004; Trostel, Walker, and Woolley, 2002 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 premium 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).

In our empirical analysis (Section 3) we find 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, and that the amount of effort supplied is in fact the key determinant of the unobserved characteristics, able to explain differences in educational performance.

We show that female students dedicate themselves more seriously to study because they gain a greater increase in labor market returns from educational performance. We interpret this as coming from a stronger signalling value for females than males, and we successfully test the hypothesis that by means of higher grades female students do signal their ability to potential employers.[4]

[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 3.1.

[4] Other researchers have argued that women receive higher grades than men because they work harder at school (Wainer and 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

2. DATA AND SUMMARY STATISTICS

Our data come from the Survey on Labor Market Transitions of University Graduates carried out in 2007 by the Italian National Statistical Office. The Survey is the result of interviewing Italians who graduated from university in 2004 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 2004 consisted of 167,886 individuals (68,939 males and 98,947 females).[5]

The ISTAT survey was based on a 16% 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 69.5%, yielding a data-set containing information on 26,570 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 overworking 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.

Table 1. Average grade by gender and field of study

Field of study	Male students	Female students	T-Statistic
Sciences	104.91	103.88	-1.89
Pharmacy	102.52	104.21	4.03
Natural sciences	105.44	106.97	4.12
Medicine	106.27	108.62	15.45
Engineering	101.88	104.53	8.21

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] The graduate students considered in this paper completed a long degree course, that is a course whose duration was four years or more, corresponding to an educational attainment of Tertiary-type A in the International Standard Classification of Education (ISCED 97).

Architecture	103.92	106.30	7.59
Agricultural studies	103.52	104.94	2.74
Economics, Business and Statistics	99.78	102.32	10.22
Political Science and Sociology	102.16	103.43	3.60
Law	97.73	99.71	6.67
Humanities	108.54	108.18	-1.17
Foreign languages	106.60	106.70	0.21
Teachers college	106.89	107.20	0.70
Psychology	102.06	103.45	2.35
Health	101.19	103.29	4.47
Total	102.81	104.98	24.04

The last column in Table 1 reports the values of the T-statistic for the Null Hypothesis that the difference between the average grades is zero. The test shows that the average grade difference between male and female students is statistically significant for most of the subjects studied.

Table 2 reports average monthly earnings and employment probability 3 years after graduation by gender and field of study. Monthly earnings in 2007 are in euros and net of taxes and social security contributions. The average earnings are 1299 and 1081 euros per month for the male and the female sub sample, respectively. The average employment probability 3 years after graduation is 0.72 and 0.63 for male and female candidates, respectively.

Therefore, on average, male graduates earn about 20% more than females and are more likely to have a job 3 years after graduation.

Table 1 shows average degree score by gender and field of study.[6] On average female students obtain higher grades in all the types of courses considered (the only exceptions being Science and Humanities). The average difference between the female and male score amounts to more than 2 points and ranges from a minimum of 0.10 for Foreign languages to a maximum of 2.65 for Engineering.

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

Field of study	Average monthly earning		Average employment probability	
	Male students	Female students	Male students	Female students
Sciences	1252.36	1065.03	0.69	0.66
Pharmacy	1280.79	1137.91	0.74	0.76

[6] 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).

Natural sciences	1232.25	1062.48	0.65	0.59
Medicine	1468.22	1234.35	0.45	0.27
Engineering	1391.70	1287.06	0.92	0.83
Architecture	1221.35	1054.29	0.87	0.82
Agricultural studies	1141.59	905.72	0.77	0.70
Economics, Business and Statistics	1349.92	1169.86	0.83	0.77
Political Science and Sociology	1300.48	1096.71	0.78	0.82
Law	1172.35	1018.93	0.60	0.51
Humanities	1107.00	948.09	0.69	0.75
Foreign languages	1204.67	1048.28	0.85	0.80
Teachers college	1062.94	961.70	0.81	0.79
Psychology	1078.69	832.67	0.72	0.70
Health	1098.13	882.75	0.78	0.74
Total	1299.28	1080.96	0.72	0.63

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 1.30% and 0.58% for male and female candidates, respectively.

Overall, we find higher grades for women in almost all types of courses on the one hand, and lower entry wages for women 3 years after graduation on the other hand.

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 (Arulampalam, Naylor and Smith, 2004; Boero, Laureti and Naylor, 2005; Micali, 2000).

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

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

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

Field of study	Male students (%)	Female students (%)
Sciences	0.73	0.00
Pharmacy	1.05	0.64
Natural sciences	0.65	0.28
Medicine	0.79	0.54

Engineering	2.03	0.21
Architecture	1.36	0.38
Agricultural studies	1.93	1.04
Economics, Business and Statistics	2.21	0.63
Political Science and Sociology	1.37	1.32
Law	1.41	0.39
Humanities	1.30	0.89
Foreign languages	0.35	1.64
Teachers college	0.73	0.73
Psychology	0.37	0.00
Health	0.71	0.35
Total	1.30	0.58

3. 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. We analyze the gender difference in educational performance by means of an ordered probit model. Following McNabb, Pal and Sloane (2002) we decompose the gender difference in educational performance in observed and unobserved inputs. Then, we focus on the unexplained part of the gender gap in educational performance (Section 3.1).

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 3.2). Moreover, we show that the marginal effect of educational performance on wages is higher for female graduates than for male graduates (Section 3.3). 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 3.4).

3.1. Factors Affecting the Gender Difference in Educational Performance

To measure the impact of gender on educational attainment, separate ordered probit models are estimated for female and male graduates. These 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. We decide to run our analysis by means of an ordered probit model. We take this approach for a twofold motive. First, the degree scores in the publicly available data are provided in brackets rather than as continuous variables. They fall into four intervals (< 79, 80-89, 90-94, 95-99) and for scores bigger than 99 the effective value is disposable. Second, if we turn our consideration to subsequent job market entry, we can reasonably accept that degree score is only a component of educational performance, the other part being represented by the speed[7] which students complete their academic career. In order to take into account both the final degree mark and the speed at which students complete their academic career, we built up a measure for educational performance: edperf.

$$edperf = \frac{dscore}{1 + 0.10 \times years} \quad \text{........} \tag{1}$$

where dscore is the degree mark plus the laude or highest honors when it occurs. The number of years in excess (years) used to get the degree 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.

We proceed in the following way. First, we identify three degree classes, g, according to the value of the educational performance. $g = 3$ corresponds to first class (high degree, high speed of completion) and it is assigned when $edperf >= 110$[8]. $g = 2$ corresponds to second class, (high degree-low speed or high speed-low degree) and it is assigned when $90 =< edperf < 110$. $g = 1$ corresponds to third class (low degree, low speed of completion) and it is assigned when $edperf < 90$. By means of an ordered probit, we estimate the probability of achieving a particular educational performance class, against selected control variables separately for male and female students.

To study the impact of gender in educational performance we follow the performance decomposition approach proposed by Jones and Makepeace (1996) and McNabb, Pal, and Sloane (2002). First, the probability of obtaining a particular degree for male and female students is obtained by:

$$\text{Prob}(1, \theta_i, x_i) = \Phi(\mu_1 - x'_i \beta) \tag{2}$$

$$\text{Prob}(2, \theta_i, x_i) = \Phi(\mu_2 - x'_i \beta) - \Phi(\mu_1 - x'_i \beta) \tag{3}$$

$$\text{Prob}(3, \theta_i, x_i) = 1 - \Phi(\mu_2 - x'_i \beta) \tag{4}$$

where Φ is the cumulative normal distribution function, x_i is the vector of explanatory variables and $\theta i = (\mu_1,i; \mu_2,i ; \beta i)$ is the vector of parameters of the ith model, for $i = m, f$ for male and female students. First, we identify the ordered probit model by excluding the constant term.[9] Second, we estimate the maximum likelihood coeffcients of the ordered

[7] In the Italian education system, each faculty only sets a minimum number 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.

[8] The upper bound limit of educational performance is 113, which corresponds to the maximum degree score, i.e. "cum laude", with no delay in completion.

[9] See Long (1997), page 124, and Verbeek (2004), page 204, for discussion of alternative parametrization to identify the ordered models.

probit, θi for the ith sample, with $i = m, f$ for male and female samples, respectively. The implied grades for male and female students are given by:

$$g_m^* = \sum_{g=1}^{3} g \Pr ob(g, \hat{\theta}_m, X_m)\ldots\ldots\ldots\ldots\ldots \tag{5}$$

$$g_f^* = \sum_{g=1}^{3} g \Pr ob(g, \hat{\theta}_f, X_f)\ldots\ldots\ldots\ \ldots\ldots \tag{6}$$

Given the expected grade for male and female students we can decompose the male-female differential in educational performance by means of the following formula:

$$g_f^* - g_m^* = \sum_{g=1}^{3} g\left[\Pr ob(g, \hat{\theta}_m, X_f) - \Pr ob(g, \hat{\theta}_m, X_m)\right]$$
$$+ \sum_{g=1}^{3} g\left[\Pr ob(g, \hat{\theta}_f, X_m) - \Pr ob(g, \hat{\theta}_m, X_m)\right]\ldots\ldots\ldots\ldots \tag{7}$$

$$g_f^* - g_m^* = \sum_{g=1}^{3} g\left[\Pr ob(g, \hat{\theta}_f, X_f) - \Pr ob(g, \hat{\theta}_m, X_m)\right]$$
$$+ \sum_{g=1}^{3} g\left[\Pr ob(g, \hat{\theta}_f, X_f) - \Pr ob(g, \hat{\theta}_m, X_f)\right]\ldots\ldots\ldots\ldots\ldots\ldots \tag{8}$$

Table 4. Regression Results from the ordered probit model of academic attainment for male and female students.

	Female	Students	Male	Students
Variable	Coefficient	T-ratio	Coefficient	T-ratio
High school mark	0.0612	38.0816	0.0604	36.1446
Subject (omitted group = Health)				
Sciences	-0.9612	-13.5444	-0.9312	-15.5031
Pharmacy	-0.6407	-13.0034	-0.5061	-8.902
Natural sciences	-0.4241	-8.1866	-0.2768	-4.5573
Engineering	-0.973	-17.2829	-1.0777	-26.3341
Architecture	-0.7056	-10.8931	-0.6551	-10.2557
Agricultural studies	-0.5826	-8.3927	-0.504	-7.0212
Economics, business and statistics	-0.8479	-21.4696	-0.9196	-21.6691
Political science and sociology	-0.5127	-11.5102	-0.4112	-7.8389
Law	-1.1759	-27.4655	-1.1243	-22.6973
Humanities	-0.3313	-6.7106	-0.1964	-3.1102
Foreign languages	-0.6566	-12.1368	-0.3866	-3.8723
Teachers college	0.2163	3.755	0.0291	0.3114
Psychology	-0.1798	-2.4795	-0.1753	-2.1362
School type (omitted group = professional school)				
Liceo	0.642	8.8215	0.5055	8.2318
Arts	0.0839	0.7949	-0.0687	-0.4787

Magistrale	0.2893	3.6263	0.2949	2.1929
Technical institute	0.2582	3.4276	0.2456	3.9039
Not born in Italy	-0.4263	-5.5547	-0.3594	-3.5173
Father's degree				
University	0.1327	3.5522	0.0078	0.1965
High school	0.0589	2.087	-0.0175	-0.5659
Mother's degree				
University	0.1726	4.1736	0.1592	3.6174
High school	0.1091	3.8888	0.1218	3.9466
Father occupational status	-0.0152	-0.3048	-0.0957	-1.6947
Father's occupation				
Manager	-0.0872	-2.1839	-0.0267	-0.657
Executive cadre	-0.017	-0.4645	0.0299	0.8085
White collar	-0.0481	-1.6812	0.0187	0.6049
Mother's occupation				
Manager	0.0524	0.5506	0.1828	1.8873
Executive cadre	-0.0506	-1.2564	-0.0039	-0.0943
White collar	0.016	0.5554	0.0157	0.5082
Possession of other degree	0.2259	3.8944	0.542	9.1193
Moved to a different town to attend university	-0.1412	-4.8669	-0.0491	-1.5816
Course attendance	0.5655	18.5627	0.4745	15.5971
Previously attended a different degree course	-0.0377	-1.1994	0.0481	1.5499
Studied in the same town of residence	0.0692	3.0101	0.0518	2.0984
Frequency of private courses during university	-0.3508	-5.0386	-0.4279	-6.0899
mu(1)	2.5619	15.7555	2.4857	15.7389
mu(2)	3.9959	24.326	3.9872	24.9067
LR Chi-Square (Coefficients equal to zero)	4966.78 (0.00)		3902.1096 (0.00)	
observations	13677		12129	

Table 4 reports the estimates of the ordered probit model of academic attainment for male and female students. Each regression includes controls for college and region of residence. P-values are represented in parenthesis.

In both equations, the first term represents the gender differential in educational performance explained by the different characteristics of male and female students. The second term takes the individual characteristics as constant but allows the parameter estimates to vary and therefore measures the unexplained variation attributable to differences in unobserved inputs.

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, dummy variables for the type of high school attended[10], and parental background in terms of occupation and education.

The second set of variables includes a dummy variable indicating whether the student moved to attend university, a dummy variable indicating working experience during university, faculty dummies and regional dummies.

Table 4 reports the main results separately for the 13677 female students and 12129 male students.[11] The model correctly predicts the degree class of about 59 % and 57 % of male and female samples, respectively. Table 4 shows the estimated coefficients of the key variables of interest. The estimated coefficients for the ordered probit model do not reject their marginal effects and, although they can be computed they are not meaningful for discrete explanatory variables such as dummy variables. As our aim is to study the effect of gender on educational performance we make use of the results reported in Table 4 to obtain the predicted probabilities that male and female students achieve different degree results, in line with the analysis of McNabb, Pal, and Sloane (2002).

Table 5 shows that for female students the probability of achieving an excellent educational performance is about 20% compared to 14% for male students. We may observe that while the predicted probabilities are shifted toward the worst levels of the educational performance, the proportion between the estimated probabilities for women and male students is mainly preserved.

Table 5. Actual and Predicted probabilities of getting a certain degree class

		Actual probability		Separate male/female regressions predicted probability			
		male	female	male using		female using	
				male equation	female equation	male equation	female equation
d=1	("poor")	45.41%	38.46%	48.32%	37.00%	50.26%	33.45%
d=2	("good")	40.75%	41.35%	46.31%	50.60%	42.88%	56.50%
d=3	("excellence")	13.83%	20.19%	5.37%	12.39%	6.86%	10.05%

Table 5 reports the actual and predicted probabilities of achieve different degree result according to the results reported in Table 4.

Table 6. Decomposition of male-female difference in academic achievement

Expected female grade	1.75		
Expected male grade	1.57		
Explained variation of excellent mark	0.015	Unexplained variation of excellent mark	0.055
Explained variation of good mark	0.034	Unexplained variation of good mark	0.077
Explained variation of poor mark	0.019	Unexplained variation of poor mark	0.132

[10] In Italy we divide between generalist education providers which correspond to the high school and the high school technical/professional relating to other types of college.

[11] 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 years.

Table 6 reports the decomposition of female-male difference in educational performance according to equation 8.

We decompose educational performance according to (7) and (8) to explain the gender gap according to observed and unobserved individual characteristics. Using the female coefficients, the probability of a male student achieving excellence increases from 5.37% to 12.39%. Similarly, when the estimated coefficients from the male equation are used to predict the distribution for female students, the probability of achieving excellence lowers from 10.05% to 6.86%.

Indeed, gender differences in degree performance have less to do with gender differences in individual characteristics, but significantly reflect differences in the way these attributes impact upon educational performance.

The results of the decomposition exercise (Table 6) show that differences in attributes are relatively insignificant in explaining gender differences in educational attainment, with only 21% of the gender gap in achieving excellence being due to differences in male and female characteristics.

3.2. 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 3.3 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 7 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 part-time students.[12] 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

[12] 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 16% of the student population - 18% of males and 14% of females); working-students (they have a part time job while studying at university and amount to 25% of the student population for both males and females); studying-students (they only study and do not work before completing their degree and amount to 59% of the student population - 57% of males and 61% of females).

engage in signalling activities because they are time constrained. 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.[13]

Table 7. OLS estimation results of the educational performance equation: full-time and part-time students

	Part-time students		Full-time students	
	Coefficient	T-Ratio	Coefficient	T-Ratio
Constant	91.860	51.018	91.150	93.511
Female	-0.024	-0.052	1.346	6.725
Subject (omitted group = Health)				
Sciences	-12.817	-8.511	-9.935	-14.728
Pharmacy	-10.498	-7.076	-8.300	-13.442
Natural sciences	-8.793	-6.396	-6.523	-10.233
Engineering	-15.360	-12.326	-11.264	-19.391
Architecture	-9.983	-6.205	-9.270	-13.673
Agricultural studies	-11.888	-7.047	-8.303	-11.669
Economics, business and statistics	-14.692	-13.588	-10.899	-19.660
Political science and sociology	-9.998	-9.032	-7.381	-12.305
Law	-16.093	-14.600	-15.113	-26.270
Humanities	-6.665	-5.486	-5.417	-8.473
Foreign languages	-10.085	-7.129	-9.398	-13.388
Teachers college	-2.393	-1.886	-2.023	-2.742
Psychology	-6.982	-4.628	-4.753	-6.085
School type (omitted group = professional school)				
Liceo	4.107	3.720	4.134	6.151
Arts	1.102	0.581	-0.458	-0.467
Magistrale	1.024	0.804	1.481	1.881
Technical institute	2.888	2.603	1.631	2.396
Father's degree				
University	-1.290	-1.611	0.935	2.725
High school	0.450	0.830	0.297	1.162
Mother's degree				
University	2.923	3.090	2.292	6.062
High school	1.381	2.444	1.397	5.470
Father occupational status	0.266	0.283	-0.343	-0.732
Father's occupation				

[13] 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 and 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.

Manager	-1.096	-1.288	-0.568	-1.535
Executive cadre	-0.541	-0.700	-0.014	-0.041
White collar	0.247	0.403	-0.210	-0.805
Mother's occupation				
Manager	4.113	1.918	0.499	0.499
Executive cadre	0.674	0.702	-0.162	-0.441
White collar	1.246	1.967	0.297	1.128
Not born in Italy	0.243	0.187	-0.960	-1.176
Moved to a different town to attend university	0.266	0.283	-0.343	-0.732
Previously attended a different degree course	0.310	0.578	-0.667	-2.164
Studied in the same town of residence	0.453	1.028	0.703	3.478
Participation in the Erasmus programme	2.628	2.978	3.626	11.287
Frequency of private courses during university	-5.086	-4.744	-5.040	-8.828
Course attendance	4.850	10.684	6.582	26.831
Possession of other degree	6.347	9.342	2.666	3.770
College dummies	X		X	
Number of observations	3496		17150	
Rbar-squared	0.25		0.19	
F	12.069 (0.00)		42.355 (0.00)	

The table reports the estimates of the educational performance equation for full-time and part-time students. P-values are represented in parenthesis.

3.3. Earnings Equation

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:

$$\ln(w) = \alpha + \beta_1 \text{ edperf} + \beta'_2 E + \beta'_3 X + \beta'_4 Z + \varepsilon \tag{9}$$

where w is the monthly wage[14], "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)

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

by controlling for self-selection in the employment status (employees versus self-employed).[15]

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 8 shows the estimation of the earnings equation for the employees and the self-employed. The results of the first-stage probit model are presented in Table 9.

Table 8. OLS estimation results of the earnings equation for the employees and the self-employed (male and female samples)

Variable	Employees				Self-employed			
	Female		Male		Female		Male	
	Coefficient	T-Ratio	Coefficient	T-Ratio	Coefficient	T-Ratio	Coefficient	T-Ratio
Constant	2.76793	86.66990	2.82793	86.40999	2.97865	15.27593	2.99794	30.41351
Lambda	0.10479	2.28157	0.05447	2.24808	0.03073	0.25800	-0.08713	-1.85779
High school mark	0.00125	3.80208	0.00091	2.82201	-0.00016	-0.11361	0.00036	0.35114
Edperf	0.00118	7.11084	0.00109	6.29654	0.00012	0.18239	0.00237	4.03741
Experience	-0.00393	-0.79974	0.01305	2.56468	0.03398	1.68187	0.00504	0.33187
Experience2	0.00063	1.15082	-0.00107	-1.94104	-0.00320	-1.40866	0.00014	0.08621
Subject (omitted group = Health)								
Sciences	0.12448	5.27034	0.12352	7.54284	0.08408	0.49164	0.17130	2.70065
Pharmacy	0.16315	7.66415	0.15759	9.73357	0.03080	0.23954	0.20328	3.37745
Natural sciences	0.11002	6.19729	0.11413	7.19558	-0.03907	-0.59175	0.07850	1.85350
Engineering	0.18169	11.41104	0.15856	11.63251	0.06171	1.13729	0.17258	4.38166
Architecture	0.05360	2.14896	0.07600	3.62497	0.00006	0.00080	0.01297	0.30243
Agricultural studies	0.03755	1.96885	0.08737	5.07171	-0.12073	-2.32304	0.05468	1.34446
Economics, business and statistics	0.15988	8.14472	0.14112	9.78075	-0.04044	-0.40584	0.16117	3.50902
Political science and sociology	0.12488	6.51321	0.09074	6.14145	-0.01778	-0.19637	0.15350	3.40032
Law	0.10326	6.72432	0.08443	5.07159	-0.02870	-0.63036	0.00233	0.06093
Humanities	0.07599	3.98304	0.02579	1.53869	-0.09394	-1.05519	0.13841	2.67445
Foreign languages	0.10074	5.12870	0.07212	3.83976	-0.10102	-1.04447	0.04924	0.68386
Teachers college	0.08856	4.10413	0.02901	1.38185	-0.23469	-1.64873	0.16216	1.53313
Psychology	-0.02221	-1.14898	0.03971	2.07527	-0.08673	-1.60654	-0.00602	-0.12557
School type (omitted group = professional school)								
Liceo	-0.00485	-0.39463	-0.01187	-0.81265	-0.03622	-0.52681	-0.12178	-1.81375
Arts	-0.03918	-2.01412	-0.02232	-0.74914	-0.03202	-0.41303	-0.01122	-0.14088
Magistrale	-0.00490	-0.36131	0.02687	0.94482	-0.01332	-0.17715	-0.16713	-1.46742
Technical institute	-0.01974	-1.57613	-0.01462	-0.99088	0.00088	0.01261	-0.12315	-1.82810

[15] 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.

Father's degree								
University	0.00152	0.20414	0.01348	1.92075	0.00928	0.30191	0.01156	0.54326
High school	0.00060	0.11633	0.00263	0.51515	-0.00678	-0.30208	0.03494	2.14228
Mother's degree								
University	-0.01208	-1.46348	-0.00782	-1.02411	0.03210	0.94298	0.00646	0.27808
High school	-0.00667	-1.25142	0.00320	0.63942	0.03690	1.53849	0.01362	0.84369
Father's occupation								
Manager	0.01689	2.16514	0.01726	2.39294	-0.00136	-0.04696	-0.00663	-0.29026
Executive cadre	0.00614	0.82253	0.01385	2.11853	-0.01535	-0.45019	0.00635	0.29560
White collar	0.00841	1.50320	-0.00064	-0.12127	0.01002	0.39986	0.00574	0.31866
Mother's occupation								
Manager	0.01330	0.63488	0.04120	2.10937	-0.07756	-1.19127	0.05833	0.90592
Executive cadre	0.01774	2.21507	0.00096	0.12666	-0.01504	-0.47555	-0.03453	-1.51569
White collar	0.00760	1.38918	0.00970	1.87554	-0.01283	-0.58933	-0.01097	-0.66139
Possession of other degree	0.03799	2.19570	0.00880	0.49054	-0.06590	-0.42220	0.03621	0.61471
Not born in Italy	0.03824	2.63407	0.02079	1.10893	0.06170	1.10988	-0.01251	-0.18824
Moved to a different town to attend university	0.01115	2.23412	0.01421	2.86238	0.04246	2.24225	0.01107	0.71835
Previously attended a different degree course	0.00592	1.26261	0.01260	3.07517	-0.02312	-1.01465	0.00639	0.47294
Studied in the same town of residence	0.00184	0.27600	-0.00124	-0.19161	0.00503	0.18430	-0.01572	-0.81105
Married	-0.00512	-1.09495	0.02442	4.85849	-0.01910	-0.98657	0.02630	1.59291
Children	-0.01857	-2.24576	0.02364	2.51965	0.02372	0.79564	-0.03246	-1.10664
Region dummies	X		X		X		X	
Number of observations	4168		3918		719		1154	
Rbar-squared	0.19		0.18		0.13		0.11	
F	17.812 (0.00)		15.764 (0.00)		1.724 (0.00)		2.486 (0.00)	

The table reports the estimates of the earnings equation for employees and self-employed. P-values are represented in parenthesis.

Table 8 shows that the magnitude of the estimated coefficient on educational performance in the employees sample is greater for females than for males.

This result is robust under several specification considered. We report here only the specification in Table 8, that is the more complete in terms of number of variables taken into account.

Moreover, Castagnetti and Rosti (2009) find very similar results using a different data set and running a slightly different methodology. Hence, these results for the Italian case seem to be robust both to a different data set and to a different econometric methodology adopted.

Table 9. First stage probit regressions for the employment/self-employment decision underlying Table 8. (1=employed, 0=self-employed)

Variable	Female		Male	
	Coefficient	T-Ratio	Coefficient	T-Ratio
Constant	0.81797	2.43000	-0.05325	-0.17000

High school mark	-0.00011	-0.05000	0.01064	3.04000
Edperf	0.00754	1.83000	0.00670	3.54000
Experience	-0.08882	-1.45000	0.11131	2.05000
Experience2	0.01125	1.64000	-0.01151	-1.94000
Subject (omitted group = Health)				
Sciences	1.31963	5.23000	0.88052	5.31000
Pharmacy	1.14268	6.70000	0.93881	6.03000
Natural sciences	0.47401	2.80000	0.07311	0.48000
Engineering	0.29605	1.89000	0.46297	3.66000
Architecture	-0.67665	-4.45000	-0.88211	-6.42000
Agricultural studies	-0.25297	-1.50000	-0.25309	-1.65000
Economics, business and statistics	0.98339	6.66000	0.76394	5.98000
Political science and sociology	0.86009	5.59000	0.50189	3.53000
Law	-0.12321	-0.83000	-0.48094	-3.58000
Humanities	0.76350	4.57000	0.40937	2.42000
Foreign languages	0.86463	5.18000	0.56733	2.71000
Teachers college	1.23232	6.10000	0.92577	3.48000
Psychology	-0.04458	-0.24000	-0.06210	-0.35000
School type (omitted group = professional school)				
Liceo	-0.14940	-0.82000	-0.31744	-1.59000
Arts	-0.29335	-1.30000	-0.04160	-0.14000
Magistrale	0.07109	0.35000	-0.26157	-0.72000
Technical institute	-0.16923	-0.91000	-0.37202	-1.85000
Father's degree				
University	-0.11117	-1.23000	-0.08988	-1.18000
High school	-0.05589	-0.83000	-0.05996	-1.03000
Mother's degree				
University	-0.12726	-1.26000	-0.03592	-0.42000
High school	-0.11135	-1.67000	-0.01597	-0.28000
Father's occupation				
Manager	-0.09540	-0.92000	-0.16421	-1.88000
Executive cadre	0.04402	0.43000	-0.15466	-1.89000
White collar	-0.00106	-0.01000	-0.09844	-1.46000
Mother's occupation				
Manager	-0.10871	-0.45000	0.30832	1.30000
Executive cadre	0.00715	0.07000	-0.05190	-0.62000
White collar	0.02326	0.34000	-0.01137	-0.19000
Possession of other degree	0.72398	2.00000	-0.08778	-0.45000
Not born in Italy	-0.34165	-2.11000	0.07130	0.31000
Moved to a different town to attend university	0.01158	0.18000	0.00522	0.09000
Previously attended a different degree course	-0.02554	-0.30000	-0.11109	-1.60000
Studied in the same town of residence	0.14785	2.59000	0.02152	0.45000
Father self-employed	-0.22213	-3.44000	-0.48634	-8.44000
Married	-0.11183	-2.01000	-0.00388	-0.07000
Children	-0.04667	-0.47000	-0.08675	-0.84000

Region dummies		X		X
Number of observations	with	4887		5072
Percent correctly predicted		86.15		80.19
McFadden's pseudo-R-square		0.19		0.17

The table reports the estimates of the probit regression of the first stage employment/self-employment decision underlying Table 8.

3.4. Human Capital versus Signalling Hypothesis

A higher return on education for females is common in literature[16], 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 labor 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, 1999).

Table 8 shows the estimation of the wage regression for employees and the self-employed.

[16] Previous findings reveal that a higher return on female education appears to be the norm in both U.S. and European countries (Card, 1999; Loury, 1997; Murnane et al., 1995). 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).

While we observe a positive selection bias for employees, the estimates do not suggest any significant selection bias for the self-employed.[17] The educational performance coefficient ("edperf") is statistically significant only for female employees. Hence, our results support the SSH, for the female sample, i.e. that educational performance has an insignificant return for the self-employed, but a significantly positive return for female employees. However, for the male sample, our results lend support neither the SSH nor the WSH. This finding is consistent with our statement that the unobserved input that causes the gender gap in educational performance is nothing but signalling effort.[18]

4. CONCLUSION

We consider the academic performance of Italian university students and their labor market position 3 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 find that a relevant part of it is due to unobserved inputs. 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 signalling or by the human capital theory. We find that the higher return on education for females comes from its signalling value.

These findings suggest a reconciliation of the stylized fact concerning the gender differential in educational performances and market earnings. Since female students have a larger (expected) signalling value for educational performances, they should be expected to rationally exert more effort than male students.

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

[18] By estimating the academic performance of Italian students who graduated in 2001, and their occupational status and earnings 3 years after graduation, Castagnetti, Chelli and Rosti (2005) find evidence that the strong screening hypothesis is strengthened, i. e. that educational performance has an insignificant return for the self-employed, but a significantly positive return for employees.

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