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Talent allocation in tournaments: The effect of gender on Italian graduate performance

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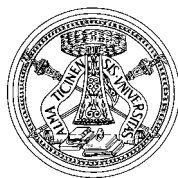
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Quaderni di Dipartimento

Talent allocation in tournaments: the effect of gender on Italian graduate performance

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Talent allocation in tournaments: the effect of gender on Italian graduate performance

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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 show 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. The rationale for this is that academic tournaments are *uneven* by gender due to the higher labour market *incremental* returns to female graduates. In other words, we reconcile the previous empirical evidence by suggesting and verifying that female students on average engage in a stronger signalling activity (so called screening hypothesis).

KeyWords: educational economics, rate of return

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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 and Kahn (2003)) even at the beginning of their careers (Kunze (2005)). In this paper we provide additional empirical evidence for the Italian graduates and we refer to a simple tournament model 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 assume the educational tournament is uneven through the different values that male and female students assign to the prizes received. In particular, we suppose the value of the tournament prize depends on the effect of educational performance on the (marginal) expected return in the

labor market and this effect differs among individuals: it is greater for females than for males. In equilibrium the model predicts that female students exert more effort than male students. Hence, female students exceed male students in the educational tournament because they offer an higher level of effort.

In the empirical analysis we attempt to confirm the assumptions put forward the educational tournament model we propose. First, we show that the most part of the difference in educational performance is explained by the difference in unobserved characteristics 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. Last, we show that female students dedicate themselves more seriously to study because they gain an higher marginal return in the labor market from success in educational competition. Our results suggest that by means of higher grades female students signal their ability to potential employers.

2 A 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:

$$U_i = K_i g_i(e) - c_i(e_i) \quad (1)$$

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 ($i, j = M, F, i \neq j$):

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

where $e = (e_M, e_F)$ is the vector of the efforts offered by students.¹ We assume that $\frac{\delta g_i}{\delta e_i} > 0$ and $\frac{\delta g_i}{\delta e_j} < 0$ 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*:

$$g_F(\cdot) = g_M(\cdot)$$

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 individu-

¹Equation (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.

als depends on their expected (*marginal*) return in the labor market, and that this return differs according to the gender.² In particular we have in mind a situation where:

$$U_i = K_i g(e) - c(e_i) \quad (3)$$

with $K_F > K_M$. This simple setup illustrates a tournament which is actually *uneven* through the prize received by the participants.³

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

$$K_F > K_M \implies e_F^* > e_M^* \quad (4)$$

Hence, an higher prize implies an 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. The key explanatory fact seems to be that female graduates face a greater increase in labor market returns from educational performance. We interpret this as evidence of a stronger signalling effect for females than males, that possibly explains the higher value female students assign to the educational tournament prize in the previous setting. The theoretical reference here is of course to the large amount of literature on the signalling effect of education (Grubb (1993); Weiss (1995); Brown and Sessions (1998); Brown and Sessions (1999); Riley (2001)).

²In 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.

³This 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: $\tilde{U}_i = g(e) - \frac{c(e_i)}{K_i}$.

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 the educational curriculum, the 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, experience in actual work, experience, type of work, net monthly wage, (iii) *Work Search*: including, kind of work desired, willingness to work abroad, preference over time table, 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 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 is represented by Science). The average difference between 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.

Table 2 reports the 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, liberal professionals 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.⁴ The dependent variable is the natural logarithm of the net monthly wage. Our specification incorporates the labor market experience and the degree score corrected by the speed at which students complete their academic career.⁵ We control also for the degree subject and the university attended. In order to capture the impact of regional differences in wages we include dummies for region of residence. Moreover, we include a dummy variable to control for workers involved in apical jobs. We include also family background variables such as the level of education, the employment status and occupation of the father. We add further information on educational attainment and work experience: work carried out during university, minimum degree score

⁴For the sake of simplicity we do not report the results of these estimations. The estimation as well as the full decomposition results are available on request from the authors.

⁵See equation (5) which defines the educational performance.

needed for present work, attainment of professional qualification. We then use the standard Blinder (1973) and Oaxaca (1973) decomposition which breaks down the overall mean gender wage gap as an "explained" component (that 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-earnings⁶ (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 lower entry wages for women three years after graduation on the other hand. Moreover, only a small fraction of the average gender wage gap is explained by observed individual characteristics.

We observe 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. Empirical evidence does, however, show a higher abandon rate for male students with respect to female students. Using data reported by MIUR (the Italian Ministry of Education, University and Research), Boero, Laureti, and Naylor (2005) find that for the three cohorts of students who entered university in the years 1998-2000, the dropout rate is higher for male students (23%) than for female students (18%). Using data reported by Istat, Micali (2000) finds that female university students drop out less often (10.3% compared to 15.4% of men), they graduate more often within the normal course time (10.6% compared to 9% of men), and they receive top grades more frequently (26.9% compared to 17.7% of men). This data confirms previous empirical research which shows that male students are more likely to drop out compared to female students (

⁶The gender wage gap is quite consistent given the fact that we are considering a first job market entry.

Arulampalam, Naylor, and Smith (2004)). Therefore, in case of selection bias, this should mainly acts against female students in the educational performance achievements.

4 Empirical analysis

In this section we apply the model to the data. In particular, we attempt either to test or to justify (when it is not possible to test) the main assumptions of the tournament model of Section 2:

1. talent is equally distributed between men and women as a group
2. The educational tournament is fair
3. the gender difference in educational performance is mainly given by the difference in effort supplied
4. female students face a stronger signalling effect of education (and this might explain why they attach an higher value than male students to educational tournament)

To assess the validity of assumption 3, our empirical analysis proceeds as follows. 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 (Section 4.3). Following McNabb, Pal, and Sloane (2002a) 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. 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 4.4).

Last, to assess assumption 4, we show that the marginal effect of educational performance on wages is higher for female graduates than for male graduates (Section 4.5). We also compare an explanation of gender difference in educational performance based on a signalling effect with an alternative explanation based on different cost of effort.

4.1 Is talent equally distributed between male and female students?

Do male and female individuals really differ in talent?

Verbal abilities and mathematical problem solving have been evaluated by psychologists in two meta-analyses (Hyde and eds. (1986); Hyde, Fennema, and Lamon (1990)). 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, and so we can reasonably assume the gender similarities hypothesis, i. e. the equal distribution of general talent between men and women as a group. However, following Hedges and Nowell (1995), the relevant issue may not be average differences but a larger variance in scores for males that leads to more males than females at the upper end of ability distribution. This finding is not evident in our case; in fact, our data shows a *first order stochastic dominance* of female students with respect to male students. Figure 1 shows the cumulative distribution functions of educational performance⁷ for female and male students. We only present results for the whole sample but we also find very similar results⁸ when we consider specific degree subjects.

⁷See subsection 4.3.

⁸The 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.

4.2 The Educational tournament is fair

Gender differences in degree performance may arise because of sex bias in both educational assessment and prejudice by male staff. Within the field of educational assessment, sex bias can occur when there are differences in the way male and female student respond to different types of assessment. Within the field of prejudice and gender stereotyping by male staff, sex bias can occur when the score given by an examiner is affected by favouritism towards students of one sex. Many studies found no evidence that systematic sex bias affects marking (Newstead and Dennis (1990); Dennis and Newstead (1994), McNabb, Pal, and Sloane (2002b)). However, some studies found 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. But, as far as we know, there is no support for the hypothesis that bias systematically discriminates against male students, and therefore we assume that educational tournaments are fair.

4.3 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 (effort and/or discrimination). 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 speed⁹ at 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*.

$$edperf = \frac{dscore}{1 + 0.10 \times years} \quad (5)$$

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* \geq 110.¹⁰ *g* = 2 corresponds to second class, (high degree-low speed or high speed-low degree) and it is assigned when $90 \leq edperf < 110$. *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 (2002a). First, the probability of obtaining a particular degree for male and female students is obtained by:

⁹In 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.

¹⁰The upper bound limit of educational performance is 113, which corresponds to the maximum degree score, i.e. "cum laude", with no delay in completion.

$$Prob(1, \boldsymbol{\theta}_i, \mathbf{x}_i) = \Phi(\mu_1 - \mathbf{x}_i' \boldsymbol{\beta})$$

$$Prob(2, \boldsymbol{\theta}_i, \mathbf{x}_i) = \Phi(\mu_2 - \mathbf{x}_i' \boldsymbol{\beta}) - \Phi(\mu_1 - \mathbf{x}_i' \boldsymbol{\beta})$$

$$Prob(3, \boldsymbol{\theta}_i, \mathbf{x}_i) = 1 - \Phi(\mu_2 - \mathbf{x}_i' \boldsymbol{\beta})$$

where Φ is the cumulative normal distribution function, \mathbf{x}_i is the vector of explanatory variables and $\boldsymbol{\theta}_i = (\mu_{1,i}, \mu_{2,i}, \boldsymbol{\beta}_i)$ is the vector of parameters of the i th model, for $i = m, f$ for male and female students. First, we identify the ordered probit model by excluding the constant term.¹¹ Second, we estimate the maximum likelihood coefficients of the ordered probit, $\hat{\boldsymbol{\theta}}_i$ for the i th sample, with $i = m, f$ for male and female samples, respectively. The implied grades for male and female students are given by:

$$g_m^* = \sum_{g=1}^3 g Prob(g, \hat{\boldsymbol{\theta}}_m, \mathbf{X}_m) \quad (6)$$

$$g_f^* = \sum_{g=1}^3 g Prob(g, \hat{\boldsymbol{\theta}}_f, \mathbf{X}_f) \quad (7)$$

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:

$$\begin{aligned} g_f^* - g_m^* &= \sum_{g=1}^3 g [Prob(g, \hat{\boldsymbol{\theta}}_f, \mathbf{X}_f) - Prob(g, \hat{\boldsymbol{\theta}}_f, \mathbf{X}_m)] \\ &\quad + \sum_{g=1}^3 g [Prob(g, \hat{\boldsymbol{\theta}}_f, \mathbf{X}_m) - Prob(g, \hat{\boldsymbol{\theta}}_m, \mathbf{X}_m)] \end{aligned} \quad (8)$$

¹¹See Long (1997), page 124, and Verbeek (2004), page 204, for discussion of alternative parametrization to identify the ordered models.

$$\begin{aligned}
g_f^* - g_m^* &= \sum_{g=1}^3 g[Prob(g, \hat{\theta}_m, \mathbf{X}_f) - Prob(g, \hat{\theta}_m, \mathbf{X}_m)] \\
&\quad + \sum_{g=1}^3 g[Prob(g, \hat{\theta}_f, \mathbf{X}_f) - Prob(g, \hat{\theta}_m, \mathbf{X}_f)]
\end{aligned} \tag{9}$$

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,¹² 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 5 reports the main results separately for the 12906 female students and 12099 male students.¹³ The model correctly predicts the degree class of about 63 % and 65 % of male and female samples, respectively. Table 5 shows the estimated coefficients of the key variables of interest. The estimated coefficients for the ordered probit model do not reflect 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

¹²In 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

¹³From 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.

effect of gender on educational performance we make use of the results reported in Table 5 to obtain the predicted probabilities that male and female students achieve different degree results, in line with the analysis of McNabb, Pal, and Sloane (2002a). Table 5 shows that for female students the probability of achieving an *excellent* educational performance is about 16% 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 shows that the distance between the probability of attaining an excellent degree class for male and female students increases when females (males) make use of the male (female) coefficients. This result seems consistent with the fact that differences in attributes are relatively insignificant in explaining gender differences in educational performance. Hence, we decompose educational performance according to 8 and 9 to explain the gender differential in educational performance according to *observed* and *unobserved* individual characteristics.

Table 6 reports the result of the decomposition exercise for average characteristics of the two samples, \mathbf{X}_m and \mathbf{X}_f . We observe that although differences in attributes are important in explaining gender differences in educational attainment, with about 36% 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 64% of the gender differences in educational attainment have to do with differences in *unobserved* inputs.

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

We claim that a large part of the 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. To isolate this effect we compare the educational performance of full time and part time students. Table 7 shows that the two estimated 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.¹⁴ Hence, the evidence of a 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, and that this is endogenously related to the labor market status.

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

To explain the previous finding, which suggests that female students exert on average a greater effort in reaching educational goals than males, we refer to the signalling role of education within the screening hypothesis¹⁵.

In signalling models employees choose the level of education necessary to signal their productivity to potential employers. Accordingly, education enhances wages and is a good investment for individuals to make (Psacharopoulos (1994)). One implication is that students in full-time jobs have less incentive to signal their ability to future employers because they have already found work. On the contrary, full-time students have an extra-payoff to be gained

¹⁴As 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.

¹⁵The screening hypothesis, in contrast to the human capital theory, attests that educational performance merely signals inherent productivity. In particular, the strong screening hypothesis states that schooling is merely a signal for employers of the productivity of an employee (Psacharopoulos (1979)) while the weak screening hypothesis states that the primary role of schooling is to signal, but that schooling also has some inherent productivity.

from excelling academically. Especially, female students may choose to signal their ability by outperforming men in terms of the grades awarded.

Before examining this hypothesis, we have to mention that the same finding could also be consistent with an alternative interpretation: female students could be characterized by a greater sense of duty or self-discipline (Duckworth and Seligman (2006)), i.e. a lower cost of effort, significantly affecting the results only when there is enough time to divide between study and leisure. We test these two alternative interpretations checking whether educational performance significantly differs 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. Table 8 confirms our guess: the female dummy (*Female*) is not statistically significant.

However, one could wonder why female students put more effort into educational signalling than male students given that they will receive lower wages and they have a lower probability of being employed. We show that even if female graduates on average earn less than male graduates, they face a greater *increase* in the labour 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,¹⁶ $edperf$ 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 for the sake of simplicity 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. We estimate the sample selection model by means of the Heckman (1979)

¹⁶The monthly wages are in euros and net of taxes and social security contributions.

two-step procedure.¹⁷

Table 9 shows that the magnitude of the estimated coefficients on educational performance (*edperf*) is always greater for the female sample. Such findings suggest that the signalling role of education is higher for female graduates than for male graduates and may account for the higher value female students assign to the educational tournament prize of Section 2.

This result provides a rationale for our statement that the unobserved input that causes the gender gap is nothing but signalling effort.

5 Conclusions

Italian data confirm that on average, even if female university students outperform male ones, working women subsequently strike shorter than men in the labor market (after controlling for observed individual characteristics). We first decompose the gender difference in educational performance between observed and unobserved factors. We find that only about 20 percent of the difference is explained by the former kind of explanatory variable. We then show that the gender difference vanishes if we consider the time-constrained part-time students, which strongly suggests that educational performance is endogenously determined by (unobserved) individual "effort". We then attempt to explain the previous (rather general) puzzling stylized facts by referring to simple results from the tournament theory. In particular, we argue and verify through testing that the labor market signaling value of academic achievements is greater for female students (i.e., the wage incremental expected value of educational performance is higher for female graduates). This suggests that in academic tournaments the "prizes" assigned have a larger (expected) economic value for female students. Thus these tournaments are in fact uneven even when fair (which we assume), implying that in the equi-

¹⁷For the sake of simplicity we do not report the results of the first stage of the probit regressions but these results are available from the authors.

librium female students should indeed exert more effort than male students, in order to make higher achievements.

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Figure 1: Cumulative Distribution Functions of Educational Performance for Female and Male Students

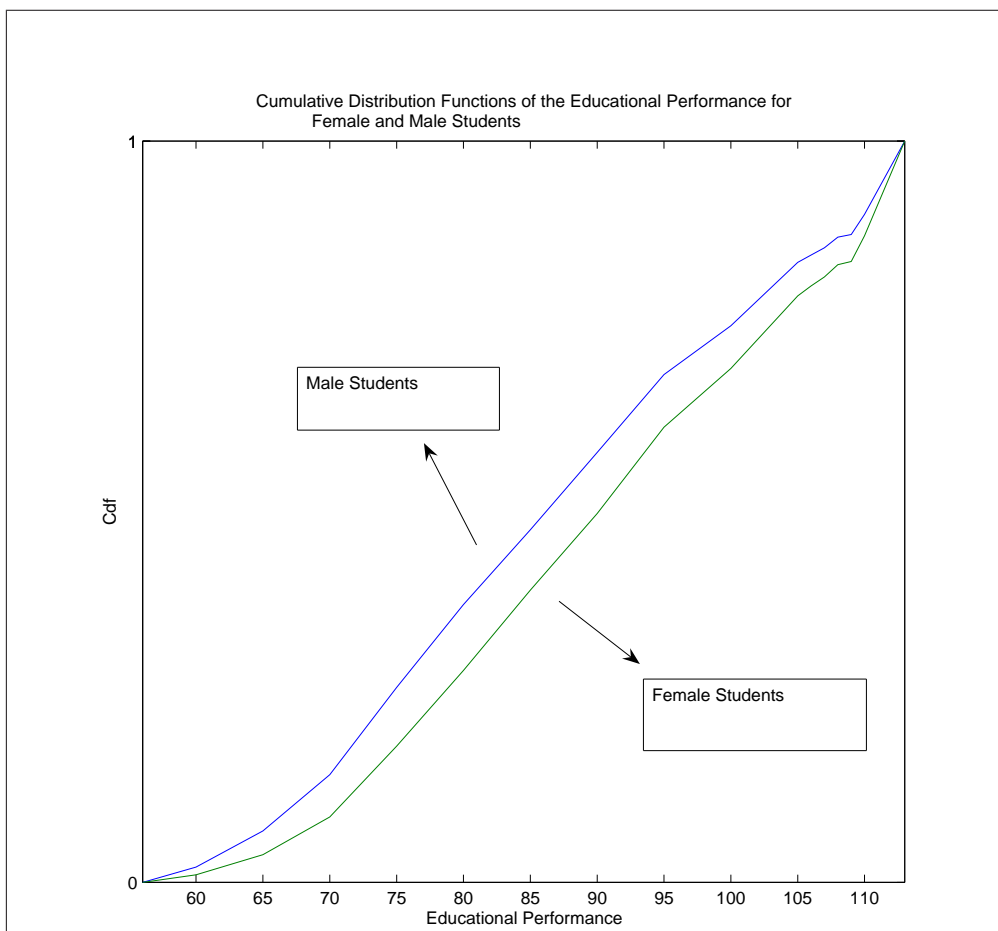


Table 1: Average grade by gender and field of study

Field of study	Male students	Female students
Sciences	102.80	102.06
Pharmacy	101.12	102.58
Natural sciences	104.29	105.66
Medicine	105.46	107.00
Engineering	100.95	103.39
Architecture	103.43	104.47
Agricultural studies	103.26	104.74
Economics, Business and Statistics	98.12	101.26
Political Science and Sociology	100.94	102.71
Law	96.16	98.99
Humanities	106.98	107.25
Foreign languages	105.12	105.60
Teachers college	105.96	106.29
Psychology	101.40	104.09
Health	107.57	107.96
Total	101.95	104.01

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.

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

Field of Study	Average monthly earning		Average monthly probability	
	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: Regression Results from the ordered probit model of academic attainment for male and female students.

Variable	Female Students		Male Students	
	Coefficient	T-ratio	Coefficient	T-ratio
Work part time during University	-0.161	-6.488	-0.154	-5.937
Work full time during University	-0.322	-7.999	-0.282	-7.208
High School Mark	0.058	33.351	0.053	30.698
<i>Subject</i>				
Sciences	-1.106	-18.805	-0.982	-17.329
Pharmacy	-0.655	-12.714	-0.580	-10.034
Natural sciences	-0.358	-7.141	-0.354	-5.741
Engineering	-1.201	-20.679	-1.159	-28.817
Architecture	-1.026	-12.854	-0.84	-11.726
Agricultural studies	-0.346	-5.230	-0.394	-6.444
Economics, Business and Statistics	-1.044	-23.249	-1.061	-22.577
Political Science and Sociology	-0.412	-7.401	-0.443	-6.925
Law	-1.113	-23.460	-1.131	-19.497
Humanities	-0.592	-12.084	-0.456	-7.405
Foreign languages	-0.874	-15.402	-0.648	-6.179
Teachers college	-0.040	-0.700	-0.045	-0.456
Psychology	-0.096	-1.379	-0.364	-4.036
father's occupational status	0.082	1.510	0.007	0.116
<i>School type (omitted group = professional school)</i>				
liceo	0.421	6.297	0.378	6.156
arts	-0.074	-0.690	-0.160	-1.122
magistrale	0.058	0.766	0.101	0.725
technical institute	0.110	1.572	0.193	3.066
previously attended a different degree course	0.073	2.089	0.083	2.391
studied in the same town of residence	0.076	3.087	0.099	3.890
moved in a different town to attend the university	-0.129	-4.068	-0.102	-3.107
siblings	-0.009	-0.284	-0.056	-1.785
frequency of private courses during university	-0.523	-6.286	-0.376	-4.465
course attendance	0.547	17.509	0.495	16.449
possession of other degree	0.641	12.643	0.709	13.598
father high education	0.033	1.386	-0.030	-1.178
mother high education	0.065	2.564	-0.018	-0.675
<i>mother's occupation</i>				
manager	0.174	1.669	0.211	1.831
executive cadre	0.202	5.780	0.115	3.150
white collar	0.098	3.272	-0.012	-0.367
not born in italy	-0.558	-3.511	-1.081	-5.443
mu(1)	2.803	15.634	2.255	13.835
mu(2)	4.037	22.333	3.457	21.027
LR Chi-Square (Coefficients equal to zero)	7197.344	(0.00)	7037.248	(0.00)
observations	12906		12099	

Table 5 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.

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 equations	female equation	female equation	male equation
d=1 ("poor")	54.69%	51.37%	68.43%	70.30%	60.95%	57.92%
d=2 ("good")	30.89%	32.40%	23.40%	22.93%	28.68%	30.15%
d=3 ("excellence")	14.42%	16.23%	8.17%	6.78%	10.38%	11.93%

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

Expected female grade	1.494	
Expected male grade	1.397	
<i>(Equation 8)</i>		
Explained variation	0.0673	36.49 % of total variation
Unexplained variation	0.1171	63.51 % of total variation
Total Variation	0.1844	
<i>(Equation 9)</i>		
Explained variation	0.0677	36.56 % of total variation
Unexplained variation	0.1176	63.44 % of total variation
Total Variation	0.1853	

Table 6 reports the decomposition of female-male difference in educational performance according to equation 8 and 9, respectively. Both explained and unexplained variations are expressed in absolute value.

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

Variable	Working during University		Not working during University	
	Coefficient	T-ratio	Coefficient	T-ratio
Constant	110.65	42.30	109.73	66.80
Female	-1.08	-1.64	3.56	14.64
<i>Subject (omitted group = Health.)</i>				
Sciences	-35.29	-18.05	-19.69	-13.84
Pharmacy	-28.53	-12.97	-15.95	-11.27
Natural sciences	-26.06	-12.53	-14.64	-10.39
Engineering	-28.85	-17.22	-21.61	-15.66
Architecture	-30.88	-13.43	-20.96	-14.42
Agricultural studies	-23.57	-8.33	-12.94	-8.83
Economics, Business and Statistics	-34.21	-23.80	-23.99	-17.56
Political Science and Sociology	-25.86	-17.83	-19.09	-13.52
Law	-36.56	-24.02	-27.84	-20.36
Humanities	-26.65	-17.75	-17.64	-12.60
Foreign languages	-33.32	-17.53	-19.49	-13.46
Teachers college	-27.15	-17.54	-14.43	-9.80
Psychology	-25.41	-12.55	-15.34	-10.49
Mother Degree	3.67	3.70	3.07	9.93
<i>School type (omitted group = professional school)</i>				
liceo	4.45	2.92	4.56	6.68
arts	-3.26	-1.12	-0.12	-0.11
magistrale	0.58	0.35	-0.69	-0.81
technical institute	1.78	1.16	2.46	3.54
studied in the same town of residence	-0.18	-0.27	0.76	3.04
frequency of private courses during university	-6.59	-4.08	-5.89	-8.59
moved to a different town to attend university	-0.12	-0.13	-1.06	-3.29
observations	2814		13640	
Rbar-squared	0.374		0.20	
F	17.494 (0.00)		34.859 (0.00)	

Table 7 reports the estimates of the OLS regression of the educational performance equation for full time and part-time students. Each regression includes controls for college and region of residence. The estimate parameters of these dummies are not reported. P-values are represented in parenthesis.

Table 8: **OLS estimation results of the educational performance equation: full-time students that are self employed at the time of the survey.**

Variable	Coefficient	T-ratio
Constant	98.71	8.79
Female	1.97	1.50
<i>Subject (omitted group = Health)</i>		
Sciences	-41.15	-3.70
Pharmacy	-29.67	-2.87
Natural sciences	-21.29	-2.20
Engineering	-31.91	-3.38
Architecture	-32.32	-3.40
Agricultural studies	-24.03	-2.46
Economics, Business and Statistics	-25.52	-2.66
Political Science and Sociology	-24.39	-2.43
Law	-35.93	-3.80
Humanities	-32.22	-3.06
Foreign languages	-17.99	-1.62
Teachers college	-24.04	-1.83
Psychology	-11.99	-1.22
Father Degree	3.60	2.32
Mother Degree	0.74	0.43
Father Occupational Status	-1.24	-0.33
<i>School type (omitted group = professional school)</i>		
liceo	7.33	1.26
arts	-5.39	-0.79
magistrale	5.02	0.73
technical institute	7.75	1.32
studied in the same town of residence	-0.89	0.39
frequency of private courses during university	-2.45	-0.66
moved to a different town to attend university	-3.58	-2.25
course attendance	6.74	4.44
not born in Italy	-10.90	-0.71
observations	688	
Rbar-squared	0.24	
F	34.5 (0.00)	

Table 7 reports the estimates of the OLS regression of educational performance equation for full time students that are self employed at the time of the survey. Each regression includes controls for college and region of residence. The estimates parameters of these dummies are not reported. P-values are represented in parenthesis.

Table 9: OLS estimation results of the earnings equation for the employees (male and female samples).

Variable	Specification 1			Specification 2			Specification 3		
	female	male	male	female	male	male	female	male	male
Constant	2.972 (143.065)	3.043 (114.988)		2.895 (104.929)	3.064 (95.011)		2.974 (102.458)	3.158 (92.749)	
lambda	-0.188 (-8.922)	-0.140 (-8.597)		-0.160 (-6.304)	-0.153 (-7.372)		0.072 (2.031)	0.016 (0.451)	
edperf	0.0006 (6.502)	0.0003 (3.249)		0.0006 (6.326)	0.0002 (2.185)		(0.0007) (7.976)	0.0004 (3.891)	
experience	0.004 (1.054)	0.013 (3.178)		0.003 (0.728)	0.013 (3.242)		0.004 (1.213)	0.015 (3.665)	
<i>experience²</i>	0.000 (0.183)	-0.001 (-1.792)		0.000 (0.224)	-0.001 (-1.859)		0.000 (-0.141)	-0.001 (-2.272)	
<i>Subject (omitted group = Health)</i>									
Sciences	0.018 (1.094)	-0.017 (-0.785)		0.032 (1.598)	-0.048 (-1.910)		0.078 (3.814)	0.000 (-0.007)	
Pharmacy	0.040 (2.465)	0.029 (1.371)		0.056 (2.872)	0.002 (0.068)		0.099 (5.010)	0.041 (1.620)	
Natural sciences	0.052 (3.170)	0.031 (1.448)		0.063 (3.207)	0.005 (0.218)		0.059 (3.083)	0.005 (0.225)	
Engineering	0.104 (6.503)	0.038 (1.851)		0.117 (5.959)	0.007 (0.301)		0.106 (5.558)	0.025 (1.036)	
Architecture	0.149 (6.643)	0.090 (3.674)		0.145 (5.247)	0.073 (2.484)		-0.005 (-0.144)	-0.044 (-1.299)	
Agricultural studies	0.019 (1.099)	0.026 (1.198)		0.024 (1.178)	0.000 (-0.008)		0.001 (0.062)	-0.029 (-1.175)	
Economics, Business and Statistics	0.036 (2.257)	0.012 (0.558)		0.052 (2.671)	-0.022 (-0.932)		0.080 (4.175)	-0.003 (-0.104)	
Political Science and Sociology	0.011 (0.655)	0.006 (0.288)		0.025 (1.294)	-0.015 (-0.590)		0.045 (2.324)	-0.004 (-0.171)	
Law	0.081 (4.806)	0.059 (2.674)		0.090 (4.415)	0.038 (1.476)		0.032 (1.525)	-0.017 (-0.626)	
Humanities	-0.015 (-0.939)	-0.043 (-1.892)		0.001 (0.071)	-0.067 (-2.591)		0.023 (1.192)	-0.055 (-2.144)	
Foreign languages	-0.019 (-1.158)	-0.013 (-0.534)		0.002 (0.119)	-0.043 (-1.601)		0.030 (1.536)	-0.055 (-2.070)	
Teachers college	-0.037 (-2.246)	-0.043 (-1.755)		-0.019 (-0.958)	-0.068 (-2.525)		0.009 (0.452)	-0.060 (-2.230)	
Psychology	0.000 (0.004)	-0.025 (-0.992)		0.018 (0.764)	-0.046 (-1.630)		-0.018 (-0.762)	-0.073 (-2.614)	
<i>School type (omitted group = professional school)</i>									
liceo	0.026 (3.118)	0.022 (2.319)		0.021 (2.473)	0.021 (2.208)		0.005 (0.565)	0.008 (0.770)	
arts	0.010 (0.668)	0.042 (1.601)		0.010 (0.695)	0.045 (1.708)		0.003 (0.205)	0.019 (0.750)	
magistrale	0.017 (1.736)	0.016 (0.659)		0.020 (2.025)	0.010 (0.417)		0.016 (1.620)	0.014 (0.576)	
technical institute	0.013 (1.490)	0.015 (1.591)		0.011 (1.238)	0.016 (1.646)		0.004 (0.420)	0.003 (0.308)	
studied in the same town of residence	0.008 (1.519)	0.015 (2.663)		0.009 (1.793)	0.014 (2.552)		0.008 (1.524)	0.002 (0.258)	
frequency of private courses during university	-0.006 (-1.869)	-0.005 (-1.422)		-0.005 (-1.395)	-0.004 (-1.182)		0.008 (2.071)	0.003 (0.922)	
moved to a different town to attend university	0.012 (3.023)	0.012 (2.890)		0.015 (3.609)	0.012 (2.699)		0.007 (1.698)	0.008 (1.854)	
married	-0.004 (-1.039)	0.011 (2.944)		-0.002 (-0.407)	0.012 (2.992)		0.009 (2.146)	0.009 (2.328)	
siblings	0.029 (2.534)	0.018 (1.284)		0.031 (2.670)	0.019 (1.398)		0.007 (0.612)	0.017 (1.264)	
College dummies		X		X	X		X	X	
Region dummies							X	X	
observations	3324	4006		3324	4006		3324	4006	
Rbar-squared	0.17	0.09		0.19	0.1		0.23	0.14	
F	25.717 (0.00)	15.52 (0.00)		9.337 (0.00)	5.848 (0.00)		9.74 (0.00)	6.533 (0.00)	

Table 9 reports the estimates of the OLS regression of earnings equation for employees. T-statistics for parameter estimates and p-value for tests appear in parentheses.