Gender, competition and career choices*

Thomas Buser
University of Amsterdam; TIER

Muriel Niederle
Stanford University and NBER

Hessel Oosterbeek
University of Amsterdam; TIER

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Abstract

Gender differences in psychological attributes, specifically gender differences in competitiveness and risk aversion are often discussed as potential explanations for gender differences in labor market outcomes. We assess the extent to which educational choices reflect academic performance and psychological attributes. Specifically, we correlate an experimental measure of competitiveness with the first important career choice of secondary school students in the Netherlands. At the age of 15, these students have to pick one out of four study profiles: a science-oriented profile, a health-oriented profile, a social science-oriented profile and a humanities-oriented profile. Choices of boys and girls show clear differences; boys concentrate in the science-oriented profile, girls in the health- and humanities-oriented profiles. We replicate the finding that boys are much more competitive than girls. We also find that competitiveness significantly affects profile choice. Gender differences in competitiveness can account for up to 25 percent of gender differences in career choices. This lends support to the extrapolation of laboratory findings on competitiveness to labor market settings.

JEL-codes: C9, I20, J24, J16
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1 Introduction

Gender differences in labor market outcomes, while greatly reduced, have remained ubiquitous. One driving source for the gender wage gap seems to be gender differences in education. To understand these gender differences in career and educational choices, psychological and socio-psychological attributes are now commonly discussed as potential explanations. While the last decade saw a flurry of laboratory evidence on gender differences on psychological attributes, the direct evidence linking the experimental literature to outcomes in the education and labor market has been rather

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scant.[1] This paper aims to close that gap. Specifically we investigate to what extent one of the most robust gender differences in laboratory experiments, gender differences in competitive attitudes, can help account for gender differences in education choices.

Gender differences in education remain an important source for gender differences in labor market outcomes. Paglin and Rufolo (1990) report that most of the gender gap in average starting salaries for college graduates is between rather than within detailed college major. Other papers confirm that the choice of college major contributes to gender differences in earnings. It is to date still the case that girls are significantly less likely to graduate from a so-called STEM (science, technology, engineering and mathematics) major than boys. In a study on the gender gap among MBA's from Chicago Booth, Bertrand et al. (2011) conclude that one of three factors that account for the large gender gap in earnings a decade after MBA completion is differences in training prior to MBA graduation, with, most notably, women taking many fewer finance courses than men. At an early educational career stage, in high school, on the other hand, girls now take as many math courses as boys (Goldin et al., 2006), and the average scores in mathematics are not very different anymore. However, girls are still less likely to take AP placement tests in science and mathematics. Furthermore, on the very highest levels of mathematics, a large gender gap remains. Ellison and Swanson (2010) provide compelling evidence that this gender gap is not driven solely by differences in mathematical ability. In mathematics, high-achieving boys come from a variety of backgrounds, while high-achieving girls are almost all drawn from a small set of super-elite schools.

In the Netherlands, where our study takes place, students are selected into tracks at the end of primary school, at age 12, with about 20 percent of the highest performing students enrolling in the pre-university track for high school. At the end of the third year of secondary school, students in the pre-university track choose between four study profiles: a science-oriented profile, a health-oriented profile, a social science-oriented profile and a humanities-oriented profile. There is a clear ranking of these profiles in terms of academic prestige, with the science-oriented profile being the most prestigious and challenging and the humanities-oriented profile being the least prestigious and challenging. Boys enroll disproportionally often into the science-oriented profile, while girls enroll disproportionally often into the health-oriented and humanities-oriented profiles. The choice of study profile in secondary school is furthermore strongly correlated with the choice of major in tertiary education which in turn is strongly correlated with future occupation and therefore with future labor market position and earnings.

We aim to assess to what extent choices of study profiles are driven by grades, expectations of how difficult mathematic is or how good a student is in mathematics, as well as psychological measures, most notably competitiveness and risk attitudes. We use competitiveness, as gender differences in competitive attitudes seem to be one of the largest and most robust gender differences found in experimental studies (see Gneezy et al., 2003, Niederle and Vesterlund, 2007 and, for an overview,

[1] Bertrand (2011) summarizes this literature and concludes: "While the laboratory evidence shows in many cases large gender differences (say, in attitudes towards risk, or attitudes toward competition), most of the existing attempts to measure the impact of these factors on actual outcomes fail to find large effects. This is undoubtedly a reflection of a rather new research agenda, as well as of the difficulty in finding databases that combine good measures of psychological attributes with real outcomes."

(Niederle and Vesterlund, 2011). For instance, Niederle and Vesterlund (2007) show that while 73 percent of men choose a competitive tournament payment scheme instead of a non-competitive piece-rate compensation for a simple arithmetic task, only 35 percent of women do so. Sutter and Rützler (2010) provide evidence that these gender differences in competitiveness are already present when children are 3 years old. That women shy away from competition while men compete too much has potentially important implications for labor market allocation. People who shy away from competitive environments may self-select into different, potentially lower paid, careers. If that is the case, too few qualified women reach the top and their positions are taken by less talented men. This result is therefore a potential explanation for the under-representation of women in certain fields such as science. As such it could explain part of the gender wage gap as documented in for example Altonji and Blank (1999) and Weichselbaumer and Winter-Ebmer (2005). Gender differences in competitiveness may in particular explain why the gender log wage gap accelerates in the upper tail, as first documented by Albrecht et al. (2003) for Sweden, and later confirmed in other studies (e.g. Arulampalam et al., 2007).

We therefore aim to assess whether gender differences in competitiveness at least partially account for gender differences in career choices. Just prior to the moment when students make their choices, we administered an experiment to elicit their competitiveness and we investigate to what extent the gender differences in study profile choices are accounted for by gender differences in competitiveness. Competitiveness is measured using the design of Niederle and Vesterlund (2007). In addition to competitiveness and performance under competition, we also collected information about students' subjectively and objectively measured ability, their (over)confidence and their risk attitudes. This allows us to correct the associations between gender differences in competitiveness and study profile choices for these factors.

As expected, we find that boys are more than twice as likely than girls to compete. We also find that competitiveness is strongly related to profile choice. Competitive students choose more prestigious profiles, where the effect is stronger for the boys than for the girls. This finding is robust to the inclusion of control variables, including grades, self-rated ability, (over)confidence and risk tolerance. Using ordered probit estimation, we find that our measure of competitiveness can explain around 25 percent of the gender difference in profile choice.

The remainder of this paper is organized as follows. Section 2 provides details of the structure of Dutch secondary education and of the study profiles. Section 3 discusses the design of our study, and Section 3.1 describes the data. Section 4 presents and discusses the results. Section 5 summarizes and concludes.

2 Academic Study Profiles in the Netherlands

The students participating in this study are drawn from the population of Dutch secondary school students who are enrolled in the pre-university track. In the Dutch school system tracking takes place when students go from primary school - grade 1 to 6 - to secondary school, normally at age 12. There are three tracks: a six-year pre-university track, a five-year general track and a four-year

Table 1. Subjects and teaching hours per study profile

Nature & Technology - NT	Nature & Health - NH
Mathematics B - 600	Mathematics A - 520
Physics - 480	Biology - 480
Chemistry - 440	Chemistry - 440
Nature, life and technology – 440	Nature, life and technology – 440
or IT - 440	or geography - 440
or biology - 480	or physics - 480
or mathematics D - 440	
Economics & Society - ES	**Culture & Society - CS**
Mathematics A - 520	Mathematics A or C - 480
Economics - 480	History - 480
History - 440	Art – 480
Management and organization – 440	or philosophy – 480
or geography – 440	or modern foreign language - 480
or social studies - 440	or Greek or Latin - 600
or modern foreign language - 480	Geography – 440
	or social studies - 440
	or economics - 480

Note: The table lists the subjects per profile and the number of teaching hours per subject during the last three years of the pre-university track. Source: Ministry of Education, Culture and Science

vocational track.[2] Around 20 percent of students graduate from the pre-university track, 25 percent in the general track and the remaining 55 percent in the vocational track. Who enrolls in which track is to a large extent determined by the score on a nation-wide achievement test administered at the end of primary school. This test consists of multiple choice questions dealing with language, arithmetic/mathematics, information processing and (optional) world orientation. It supposedly measures students' cognitive ability. Our sampling frame consists of the 20 percent pre-university track students.[3]

Halfway through the six years of secondary school, in grade 9, students in the pre-university track have to choose one out of four study profiles: the science-oriented profile Nature & Technology (NT), the health-oriented profile Nature & Health (NH), the social science-oriented profile Economics & Society (ES) and the humanities-oriented profile Culture & Society (CS). Table 1 shows the subjects that differ across the different study profiles and the number of teaching hours assigned to these subjects in the last three years of secondary school.[4] Mathematics is is taught in each track, but at different levels; A, B, C and D, where D is the most advanced followed by B, A and C.

Some schools also allow for combined profiles, namely ES/CS and NT/NH. In the ES/CS profile, students replace one of the CS-electives with the economics course. In the NT/NH profile, students

[2]The latter is divided into different sub-tracks which differ in the shares of school-based and work-based learning.

[3]Girls are somewhat more likely to go to the pre-university track, making up 54 percent of the students (source: Statistics Netherlands (CBS)).

[4]In addition the students take the following non-profile specific subjects: Dutch (480 hours), English (400), second foreign language, Latin or Greek (480), social studies (120), general natural sciences (120), culture (160), sports (160). The students spend roughly half their time on profile specific subjects and half on common subjects.

Table 2. Undergraduate major by profile (percentages)

	NT	NH	ES	CS
Humanities	9	6	8	30
Social Sciences	2	9	19	34
Law	1	4	20	20
Economics and Business	15	8	46	5
Science and Engineering	64	18	2	0
Health Care	7	48	1	1
Other	2	7	4	9
Going to university	81	72	69	60
Profile Choices				
Boys	35	21	38	6
Girls	10	34	32	24

Source: Statistics Netherlands (CBS). The data from the top rows are from 2006. The data from the bottom rows are from 2009, where we exclude choices of combined profiles.

take the hardest mathematics version, Mathematics B, albeit only at 520 hours. Furthermore, Physics is not required. As such, the combined profiles are somewhat in between the pure profiles, though a little closer to ES and NT, respectively.

The choice of study profile in secondary school is strongly correlated with the choice of major in tertiary education.[5] Table 2 shows for each study profile the distribution of students across undergraduate majors. Most NT graduates study a subject in science and engineering, NH graduates often opt for health-related subjects, ES graduates often choose a major in economics and business or in law, and most CS graduates choose a subject in the humanities, social sciences or law.[6]

Different study profiles are not only associated with different careers, they also differ in the chance with which students in each profile enroll in university. While 81 percent of NT students continue their education at the university level, only 60 percent of CS students do so. This ordering of study profiles also corresponds to how the profiles are viewed. NT is generally regarded as the most challenging and highest-reward study profile, followed by NH and ES, and CS as the least demanding and lowest-reward study profile.

Girls in year three of the pre-university track overall perform somewhat better than the boys. They are, for instance, less likely to drop out or repeat a year. In standardised tests such as the PISA test[7], girls and boys perform similarly whereby boys do slightly better at maths and girls slightly better in other subjects.[8]

Despite the similarities between boys and girls, they make very different study profile choices.

[5] Undergraduate systems in European countries are different from the US. In the US, people start by sampling lots of courses, then decide on a major later. In Europe, students choose a major from the beginning of their studies and only have major-relevant courses.

[6] The study choices of combined students look as follows: Humanities (3%), Social Sciences (5%), Law (3%), Economics and Business (5%), Science and Engineering (39%), Health Care (19%), Other (24%).

[7] Programme for International Student Assessment; an evaluation in OECD member countries of 15-year-old school students' academic performance.

[8] Source: Driessen and Van Langen (2010).

Table 3 shows that boys are more likely to choose more prestigious study profiles. Compared to girls, boys are more than three times as likely to choose the most prestigious profile, NT, and less than a third as likely to choose the least prestigious profile, CS. The fact that girls are disproportionately more likely to choose CS has prompted a debate with the minister for education even proposing to eliminate the profile altogether. This idea was ultimately rejected and the profiles are to stay as they are for a while to come.[9]

3 Experimental Subjects and Design

The aim of this paper is to assess the extent to which psychological attributes, most notably competitiveness, can account for gender differences in academic profile choice in the Netherlands. This can serve as a test to show that psychological attributes can account for gender differences in labor market outcomes. We investigate the extent to which classic channels such as grades and gender can account for choices, as well as psychological channels, such as competitiveness, confidence and risk attitudes. To achieve this we focus on a small set of students in the Netherlands that are about to choose their study profiles. We assess their psychological attributes through class experiments. This information is complemented with information collected through a short questionnaire and administrative data provided by the schools. We first describe the environment and the participants in our study, followed by the experimental design to assess psychological traits.

3.1 The Environment

We invited secondary schools in and around Amsterdam to participate in a research project investigating the determinants of academic profile choices. We demanded one class hour (45 or 50 minutes) of all classes in 9th grade, the 3rd grade in the pre-university track. The invitation letter stated that students would participate in an experiment and be paid depending on their choices.

Four schools cooperated, one in the city of Amsterdam and three in cities close to Amsterdam. In each school, we captured all students in the 3rd grade of the pre-university track, that is students could not self-select into the experiment. The number of classes per school varied from 3 to 5; in total we have data from 16 classes. A total of 397 students participated in the experiment.

After the end of the school year, the schools provided us with the final grades, including mathematics, and the definite profile choices of each student. For 35 students we do not have a definite profile choice.[10] For 20 of these students, we use the profile choice from the questionnaire.[11] We drop the remaining 15 students for whom we have neither a final choice nor a clear choice from the questionnaire. We have to drop an additional 4 students from the analysis because they showed up late to class and missed part of the experiment, 2 students because their questionnaires were

[9] Source: http://nos.nl/artikel/203421-minister-wil-onderwijs-reorganiseren.html and http://nos.nl/artikel/268284-raad-niet-minder-profielen-havovwo.html

[10] Some students may have to retake the year, and in some schools those are included in the final profile choice, in some not.

[11] For the students for whom we have both the final profile choice and the intention stated in the questionnaire, the questionnaire answer accurately predicts the final choice in 94 percent of the cases.

incomplete and they therefore lack key control variables, and 14 students because we did not obtain their grades. This leaves us with a sample of 362 subjects.

3.2 The Experimental Design

We use a classroom experiment to obtain an individual measure of competitiveness. The design closely follows Niederle and Vesterlund (2007). Participants perform a real task, first under a noncompetitive piece rate scheme and then under a competitive tournament scheme. Participants choose which of the two payment schemes to apply to their third and final performance. This allows us to determine the extent to which the choice of compensation scheme depends on performance.

The task of the experiment is to add up sets of four two-digit numbers for three minutes. The performance in each round corresponds to the number of correctly solved problems. In each round participants received envelopes that contained a sheet of 26 problems. After having read out the instructions that were on top of the envelopes and answering potential questions, the experimenter gave the signal subjects could open the envelopes and start the addition problems. Participants were not allowed to use calculators, but could use scratch paper. At the end of three minutes subjects had to drop the pen and stand up. In each round there were three versions of the 26 addition problems to prevent copying from neighbors.

Participants were informed they would perform in three rounds, one of which was randomly chosen for payment at the end of the experiment through the roll of a die in front of the class. Participants received details on each round only immediately before performing in the task. Students did not receive any information on the performance of anyone else and were paid, a week later, through sealed envelopes. Participants earned on average €5.55, with a minimum of zero and a maximum of €25.

Participants first performed the task under a noncompetitive piece rate of 25 Euro-cents per correctly solved problem. In round two they performed in tournaments of four, where the three competitors were randomly selected among students from the same class by computer after the end of the experiment. The person with the largest number of correctly solved problems was paid €1 per correct problem and the others received no payment. In case of a tie, the winner was randomly determined. Participants did not receive any information about their own performance or the performance of others, including whether they won or lost the tournament, since their competitors where only determined after the experiment.

In the third round, participants chose which of the two payment schemes they would prefer. A participant who chose the piece rate received 25 cents per correct problem. A participant who selected the tournament would win if his or her new round 3 performance exceeded the performance of the other three group members in the previous round 2 tournament. Therefore, just like in Niederle and Vesterlund (2007), the choice was an individual decision as participants could not influence the payoffs of any other participant.[12]

[12]There are several advantages to having participants compete in round 3 against the previous round 2 tournament performance. First, the performance of a player who chose the tournament is evaluated against the performance of other players in a tournament. Second, the choice of compensation scheme of a player does not depend on the choices

Since the choice of compensation scheme may depend on the participants' beliefs about their relative performance, we elicited these beliefs after the round 3 performance. Specifically, we asked students about their relative performance in the round 2 tournament compared to the other three group members. If their guess was correct, they received €1.[13]

A final factor that may influence the choice of compensation scheme are attitudes towards risk. We elicited risk attitudes by using two measures. First, following Eckel and Grossman (2002), subjects picked one option among a sure payoff of €2 and four 50/50 lotteries with linearly increasing riskiness and expected payoffs: 3 or 1.5; 4 or 1; 5 or 0.5; 6 or 0. The outcome of the lottery is determined by a dice roll at the end of the experiment.

Second, we asked subjects "How do you see yourself: Are you generally a person who is fully prepared to take risks or do you try to avoid taking risks?" The answer is on a scale from 0 ("unwilling to take risks") to 10 ("fully prepared to take risk"). This second risk measure has several advantages and disadvantages. First, it is simply a survey question, which makes it cheap, but potentially less reliable. However, Dohmen et al. (2011), using representative survey data from Germany, find that this simple question predicts both choices in a lottery task and risky behavior across a number of contexts including holding stocks, being self-employed, participating in sports, and smoking. Lonnqvist et al. (2010) find the question to be much more stable over time than lottery measures for risk attitudes. A second issue is that it is not completely clear what the question measures. While it may measure risk attitudes, it may also measure preferences for competition. Consider two individuals that have the same risk attitudes, but one is more willing to enter competitions due to higher competitive attitudes. This latter person may answer that they are more willing to take risks than the former, because they are more willing to enter tournaments to satisfy their competitive attitudes, which inherently entail more risky prospects. We will study the extent to which this question correlates with risk aversion, decisions to enter competitions and, eventually, study profile choices.

The experiment concluded with a questionnaire. Since mathematical ability can be expected to be an important factor when choosing academic profiles, we ask students to rank themselves on mathematical talent compared to other students in their year (and school) on a scale from 1 (the best 25%) to 4 (the worst 25%).[14] We also asked students how difficult they find it to pass their math class on a scale from 0 (very easy) to 10 (very hard).[15] Finally, we asked students which profile they expect to choose in June, several weeks after the experiment. The experiments were conducted in March, April and May of 2011.

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of other players. Third, the participant provides no externality to another subject, hence motives such as altruism, or fear of interfering with someone else's payoff play no role.

[13]When two subjects have the same number of correctly solved additions they receive the same rank. For example, if two subjects are tied for first place, they are both ranked first and receive €1 if their guessed rank is equal to 1. The next best subject is ranked third.

[14]This was phrased as three yes/no questions: "Do you think your mathematics ability is in the top 25% of your year?", "...top 50% of your year?", "...top 75% of your year?". A student who answered all 3 questions with a no was automatically assumed to be in the bottom 25%. We had 44 students who answered no to all questions. A student who answers yes to one of the questions also should answer yes to the next (if one is in the top 25%, one is also in the top 50%). 67 students, however, switched back to no. For these students, we count the first yes as their true answer.

[15]"How difficult is it for you to pass the math class?" (on a scale from 0 - very easy - to 10 - very hard).

Table 3. Descriptive statistics about profiles

	NT	NH	ES	CS	
All: Prestige (% rank)	1.48 (71%)	2.13 (57%)	2.64 (60%)	3.67 (81%)	
Boys: Prestige	1.43 (75%)	2.24 (57%)	2.59 (56%)	3.68 (82%)	
Girls: Prestige	1.52 (68%)	2.03 (57%)	2.71 (64%)	3.66 (80%)	
By chosen profile					Difference
GPA (1-10)	7.12	7.11	6.63	6.51	0.00
Math grades (1-10)	7.25	6.73	6.20	6.21	0.00
Math difficulty (0-10)	1.95	3.62	4.90	5.30	0.00
Math quartile (1(best)-4)	1.52	1.98	2.50	2.67	0.00
Observations	102	89	128	43	

Note: Top rows: Average ranking of study profiles, and in parentheses, the fraction of students who rank that profile first (for NT), second, third or fourth for NH, ES and CS, respectively. Bottom rows: Average characteristics for subjects who chose that profile. Last column reports p-values from Kruskal Wallis tests.

4 Results

We present the results in three stages. First, we describe the study profile decisions of participants and the effect of grades on gender differences in choices. Second, we assess gender differences in competitiveness. We analyze whether other psychological attributes such as confidence and risk attitudes can account for gender differences in competitiveness. Gender differences in (over-)confidence and risk attitudes can both explain a substantial part of the gender differences in tournament entry but still leave a large part unexplained. In the main result section we examine to what extent gender differences in competitiveness can account for gender differences in study profile choices. The competitiveness measure from the experiment significantly affects profile choice even conditional on real and perceived ability. The key finding is that gender differences in competitiveness can account for around 20 percent of gender differences in study profile choices. In the last part we decompose the effect of competitiveness on study profile choices into competitive attitudes, confidence and risk attitudes. The most important and robust psychological attribute is competitiveness.

4.1 Profile Choices and School Data

We first describe the profile choices as well as the grades and questions relating to mathematical prowess of the 362 students in our sample. Two of the four schools in our sample allow students to pick the combined profiles. Of the 173 students in those two schools, 18 pick the CS/ES combination and 64 students choose the NT/NH combination. For the main analysis of this paper we use the chosen profile as stated in the questionnaire to split the NH/NT and ES/CS combination choices into NH and NT and ES and CS decisions, respectively. However, since one can argue that the NT/NH profile is closer to NT, and the ES/CS closer to ES, we reestimate all regressions using this alternative definition of profile choice (where we have to drop an additional 20 students for whom we do not have a final profile choice). Lastly, as a further robustness check, in the appendix, we show results where we treat NT/NH and ES/CS as separate categories.

Table 4. Descriptive statistics by gender

	Boys	Girls	Gender-dif.
GPA (1-10)	6.76	6.97	0.01
Math grades (1-10)	6.67	6.59	0.64
Math difficulty (0-10)	3.41	4.18	0.01
Math quartile (1-4)	1.97	2.25	0.00
Profile Choice			
Nature & Technology (NT)	.40	.17	
Nature &Health (NH)	.12	.36	
Economics &Society (ES)	.39	.32	
Culture & Society (CS)	.08	.15	0.00
Observations	177	185	

Note: Last column reports p-values from Wilcoxon ranksum tests (except for profile choice where Fisher's exact test was used).

Before showing the profile choices of students, we confirm that the students in our sample rank the four profiles in the predicted order. We asked the 362 secondary school students in our sample to rank the four study profiles by asking "Which profile do the best students pick?". Their responses concur with the general opinion. The first row of Table 3 shows that the average rank follows the expected pattern, with NT having the best average rank, followed by NH and ES, and CS having the worst average rank. Furthermore, a majority of over 70 percent of students believes NT is the most demanding study profile. A majority of students ranks the NH study profile second and ES third. Finally, more than 80 percent of the students rank CS as the least demanding profile. As Table 3 shows, the rankings of boys and girls are remarkably similar. We also asked students to rank the four study profiles in terms of future earnings.[16] The picture that emerges is very similar; for NT the mode is the first rank, for NH the mode is the second place, for ES the mode is the third place and few students disagree that CS is the study profile with the poorest earnings prospects.[17]

The second part of Table 3 shows descriptive statistics by study profile. The choices conform with the view that higher performing children are more likely to choose more prestigious profiles. This is true both for the overall GPA, which is computed as the average of all grades, including mathematics, as well as just for the mathematics grade. Likewise, students that choose more prestigious profiles find mathematics less difficult (0 - very easy to 10 - very hard) and believe they are more likely to be among the highest ability children in mathematics (1 - best 25% to 4 - worst 25%).

Given that higher performing children choose more prestigious study profiles, we now assess academic differences between boys and girls in our sample in Table 4. On average, girls have a higher GPA than boys. In mathematics, there are no gender differences in performance. Despite this fact, girls say that they find it more difficult to pass the mathematics class, and they rank

[16]The exact question was "With which profile do you think you would earn most in ten year's time? Rank the profiles from 1 to 4 where 1 means that you would earn most if you chose that profile and 4 that you would earn least if you chose that profile. This question was only asked to students in two of the four schools and the percentages are therefore based on 181 observations.

[17]50% think that NT gives the best salary prospects, 27% think NH, 20% ES and 2% CS.

Table 5. Gender and profile choice

	(1)	(2)	(3)
Female	0.342***	0.449***	0.329***
	(0.114)	(0.121)	(0.123)
Math Grade		-0.188	-0.016
		(0.133)	(0.141)
GPA		-0.360***	-0.326***
		(0.105)	(0.109)
Rel. Math Gr.		0.509	0.345
		(0.475)	(0.484)
Math Difficulty			0.336***
			(0.075)
Math Quartile			0.076**
			(0.031)
Cut 1	-0.404	-3.957	-1.766
Cut 2	0.251	-3.205	-0.948
Cut 3	1.367	-1.961	0.392
N	362	362	362

Dependent variable: Profile choice, where NT<NH<ES<CS. Coefficients in Columns (1) to (3) from ordered probit regressions; coefficients in Columns (4) to (6) from OLS regressions; standard errors in parentheses; *, ** and *** denote significance at 10, 5 and 1 percent, respectively.

themselves as less likely to be among the high ability mathematics children in their school.

While academically boys and girls are very comparable, girls make significantly different profile choices from boys. The lower part of Table 4 shows profile choices by gender in our sample of 362 students. The pattern is similar to the pattern observed in national statistics. The NT profile is much more popular among boys than girls, while the opposite holds for NH. The ES profile is slightly more popular among boys than girls, and girls are more likely than boys to choose the least prestigious profile, CS.

To more precisely understand gender differences in profile choice, we show in Table 5 ordered probit regressions where we order profiles by NT<NH<ES<CS. The first column shows that girls are significantly more likely to choose a less prestigious profile. We then include academic variables such as overall GPA, the mathematics grade and the mathematics grade compared to other children in the same class.[18] When we include these three academic achievement variables, the gender gap actually increases by about one third. When we add the students' beliefs about their underlying mathematics ability and their belief about how good they are at math compared to their peers, the gender gap shrinks again but remains large and highly significant. While these additional variables may already be viewed as psychological attributes, it may well be that they produce an additional

[18]To compute the relative mathematics rank in class, we include all 397 students in our sample, including the 35 students we had to drop for the final results. Specifically, we gave the best students in class a rank of 1. The rank of each student is equal to 1 plus the number if students with a better grade. We then normalize the measure by dividing by the number of students in the class.

insight into a students' real mathematical ability compared to grades only. In any case, there is a significant gender difference in study profile choice, with girls choosing less prestigious profiles than boys.

Table 10 in the appendix shows that the results are very similar when we classify an NT/NH combi choice as NT, and an ES/CS choice as ES, instead of using the students' answer in the questionnaire to attribute combi profile choices to one of the four baseline study profiles. The results are also robust to treating the combi profiles as their own category, where combi profiles are ordered between the baseline study profiles, that is, NT<NT/NH<NH<ES<ES/CS<CS.

Second, we run probit regression on choosing the most prestigious profile, NT, compared to any other profile. We compute the marginal effects evaluated at a male student and average values for the other five variables we used in column (3) of Table 5. We find that girls are 23 (s.e. 0.05) percentage points less likely to choose NT, a significant difference (p = 0.00). When we redo the exercise for choosing the least prestigious profile, CS, compared to any other profile, the marginal coefficient shows that female students are 0.07 (s.e. 0.03) percentage points more likely to choose CS than boys, controlling for grades and feelings about mathematical prowess, a significant difference (p = 0.03).

To summarize, boys and girls in our sample, despite similar grades, differ vastly in their study profile choices, with girls choosing significantly less prestigious profiles. In the next section we assess psychological attributes of the students in our sample. We will then use those attributes to assess whether they can account for gender differences in study profile choices.

4.2 Gender differences in competitiveness and other psychological attributes

While the students in our sample have been filtered on the basis of their score in the achievement test in primary school, all students enrolled in the pre-university track have until this stage been exposed to exactly the same curriculum. Hence, differences in competitive attitudes at this stage cannot be the result of differences in exposure to, or experiences in, for example, different study programs. More specifically, we do not have to worry that any differences between students across study profiles are due to the exposure to different teachers, classmates and so on. We can therefore assess psychological attributes of students that, in turn, may influence the decision on study profile choice.

We analyze the gender competition data of the 362 students in our sample. While 397 students participated in the experiment, we addressed why we had to exclude 35 of them. Those students, however, participated in the round 2 tournament of our experiment. So, while we drop them from the description of results, we, of course, use their data when calculating relative measures in the experiment, such as chances of winning, the accuracy of the guessed rank and the relative math grade.

The average performance of boys in the Round 1 piece rate is 6.60, significantly larger than the 5.94 of girls (p = 0.03 using a two-sided t-test).[19] In the round 2 tournament, there is no

[19] When we use a non-parametric Mann-Whitney test, all results are basically the same.

Table 6. Determinants of tournament entry

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
Female	-0.264***	-0.260***	-0.235***	-0.190***	-0.250***	-0.193***	-0.166***	-0.169***	-0.143**	-0.153***	-0.141**
	(0.049)	(0.051)	(0.052)	(0.055)	(0.051)	(0.055)	(0.055)	(0.055)	(0.057)	(0.056)	(0.057)
Tournament		0.055***	0.047**	0.025	0.051**	0.021	0.023	0.019	0.014	0.026	0.016
		(0.020)	(0.020)	(0.021)	(0.020)	(0.021)	(0.021)	(0.021)	(0.020)	(0.022)	(0.021)
T - PR		-0.028**	-0.027**	-0.022*	-0.028**	-0.021	-0.018	-0.017	-0.016	-0.018	-0.014
		(0.013)	(0.014)	(0.013)	(0.013)	(0.014)	(0.014)	(0.014)	(0.014)	(0.014)	(0.014)
Win Prob		0.213	0.295	0.030	0.238	0.054	0.007	0.031	0.102	-0.038	0.063
		(0.207)	(0.209)	(0.213)	(0.209)	(0.218)	(0.214)	(0.219)	(0.221)	(0.218)	(0.230)
Math grade			0.118**						0.125*		0.141**
			(0.058)						(0.065)		(0.067)
GPA			-0.131**						-0.131**		-0.120*
			(0.058)						(0.059)		(0.062)
Math Relative			-0.047						0.111		0.076
			(0.223)						(0.240)		(0.249)
Guessed rank				-0.293***		-0.302***	-0.293***	-0.301***	-0.292***	-0.275***	-0.269***
				(0.044)		(0.043)	(0.043)	(0.043)	(0.043)	(0.044)	(0.044)
Math quartile					0.006	0.060		0.061	0.060		0.069
					(0.039)	(0.042)		(0.043)	(0.042)		(0.043)
Math hard					-0.022*	-0.017		-0.019	-0.010		-0.009
					(0.013)	(0.014)		(0.014)	(0.015)		(0.016)
Lottery							0.075***	0.076***	0.081***	0.033	0.037
							(0.023)	(0.023)	(0.023)	(0.024)	(0.025)
Risk-taking										0.082***	0.089***
										(0.019)	(0.019)
N	362	362	362	362	362	362	362	362	362	362	362

Dependent variable: Round 3 choice of compensation scheme (1-tournament and 0-piece rate). The table presents marginal effects of the coefficients evaluated at a male student with a 0.25 chance of winning (the rest of the variables are evaluated at the sample mean). Standard errors of the marginal coefficient are in parentheses; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$ of the underlying coefficient.

significant difference in performance, boys correctly solve on average 7.90 problems, compared to 7.42 for girls (p=0.15). Since students compete only against students in their own class, we compute for each student the chance to win the Round 2 tournament given their performance and that of their classmates.[20] For boys, the average chance to win the tournament is 28%, which is not significantly different from the 25% chance of girls (p=0.23). Provided the performance in Round 3 is not lower than that in Round 2, then every student with a chance of winning the tournament of 25 percent and higher has higher earnings when choosing to enter the tournament in Round 3. This would result in 40 percent of the boys and 36 percent of the girls entering the tournament (p = 0.26, Fischer's exact test). We find that 49 percent of boys and only half as many, 23 percent, of girls enter the tournament, a significant difference (p = 0.00, Fischer's exact test).

Table 6 shows marginal effects of a probit regression of tournament entry in Round 3. Girls have a 26 percentage point lower probability of entering the tournament compared to boys, when controlling for performance in the Round 2 Tournament, the improvement in performance between the Round 1 Piece Rate and the Round 2 Tournament, and the chance of winning the tournament. These results are very much in line with those of Niederle and Vesterlund (2007) and the large resulting literature (see Niederle and Vesterlund, 2011).

Since the performances are measured in an addition task, we add in column 3 the math grade, the GPA and the relative math grade in the class. The gender gap in tournament entry is barely affected, and remains at 24 percentage points.

The decision to enter the tournament may also depend on beliefs about relative performance. We therefore asked students to rank their relative performance in the Round 2 tournament from 1 (for best) to 4 (worst) of their group of four. Students received € 1 if they guessed their rank correctly. The average guessed rank is 2.14 for boys, and 2.56 for girls, the distribution being significantly different (p=0.00; Fischer's exact test). We find that 32 percent of the boys and 11 percent of the girls believe that they are the best performers within their group, a significant difference (p = 0.00 Fischer's exact test). To assess those beliefs, we compute for each student the optimal guessed rank, that is, the guess that would have maximized their expected earnings, given the performances of the other students in their class.[21] While 56 boys and 21 girls belief they have the highest performance in their group, the numbers would be 60 and 56 when we use the optimal guessed rank. Using the optimal guessed rank, there is no gender difference in optimal beliefs, which average 2.23 for boys and 2.34 for girls (p=0.51, Fisher's exact test). Despite this, an ordered probit regression of the guessed rank on the optimal guessed rank and a female dummy delivers a female coefficient of 0.522 (s.e. 0.118, p = 0.00).[22] This confirms that girls, given their relative performance, are significantly less confident about their relative performance than boys.

[20]To compute the chance of winning the tournament for each participant, we use simulations and randomly draw one thousand different comparison groups of three from a participants' own class. If two performances were tied for first place, a 0.5 win was assigned (1/3 in case of three tied performances and 0.25 in case of four).

[21]We compute the optimal guessed rank through simulation. We randomly draw a thousand different comparison groups of three from a participants' own class. We counted the number of times a student ranked first, second, third and fourth. The mode of the ranks is the best guess as it maximizes expected earnings. If two performances were tied for first place, a 0.5 win was assigned (1/3 in case of three tied performances and 0.25 in case of four).

[22]The coefficient on the optimal guessed rank is 0.621, s.e. 0.061, p=0.00.

Adding the guessed rank to the probit regression on tournament entry in Table 6 shows that the gender coefficient drops by about 30 percent and is now 19 percentage points and still very significant. Since the task is a mathematics task, we could, instead, use the students' beliefs about their relative performance in mathematics and their beliefs about their math ability. This, however, reduces the gender gap only by about 4 percent and a gap of 25 percentage points remains (see column 5). Adding all measures on beliefs about one's relative performance and math prowess does not reduce the coefficient on female much compared to just having the guessed rank. Female students are then 19 percentage points less likely to enter the tournament (see Column 6).

Finally, the decision to enter a tournament as opposed to opting for a piece rate payment may also depend on risk preferences. However, in their survey article, Niederle and Vesterlund (2007) have not found strong evidence that risk attitudes account for the choice of tournament. The incentivized risk measure is a choice among lotteries, where 1 is the risk free choice of €2 and 5 is the choice to receive €6 with a 50 percent chance.[23] Boys are significantly more likely to make risky choices; they choose on average 3.46 compared to 2.99 for girls, a significant difference ($p = 0.00$; t-test). Adding this risk measure to performances and beliefs on relative performance further reduces the gender gap in tournament entry by 2 percentage points to 17 percentage points (compare columns 4 and 7).[24]

As a second risk measure we simply asked students to evaluate themselves whether they are "generally a person who is fully prepared to take risks or do you try to avoid taking risks?" The answer is on a scale from 0 ("unwilling to take risks") to 10 ("fully prepared to take risk"). Boys answer on average 6.52 compared to 5.96 for girls, a significant difference ($p=0.00$; t-test).[25] Apart from not being incentivized, it is not completely clear whether this risk measure does not, also, embed a measure of competitive attitudes as we discussed in section 3.2. We show in Table 6 the effect of adding this additional risk measure, however with the reservation that it may also reflect an additional measure of competitive attitudes. Compared to the regressions using only the lottery measure, the additional reduction in the gender gap is small (compare columns 7 and 10). But when both risk measures are added, only the questionnaire measure stays significant indicating it has greater predictive power for tournament entry than the lottery measure.

In summary, the students in our sample follow the standard gender differences in choice of competition (see Niederle and Vesterlund, 2011). Controlling for performance, girls are about 24 percentage points less likley to enter a tournament. Boys have significantly more optimistic views about their relative performance than girls, and these gender differences in confidence account for about one third of the gender gap in tournament entry. Risk attitudes, whether measured by a lottery choice or a simple questionnaire item, also significantly predict tournament entry.[26]

[23] The remaining three lottery choices are 2, 3 and 4 for the 50/50 lotteries with linearly increasing riskiness and expected payoffs: 3 or 1.5; 4 or 1; 5 or 0.5.

[24] When we add only the lottery choice without the belief measure, the marginal effect on female is 0.21 (s.e. 0.056 and $p=0.00$ of the underlying coefficient).

[25] The correlation between the two risk measures is 0.42 in the whole sample, and 0.45 and 0.34 in the sub-samples of boys and girls, respectively.

[26] Although Niederle and Vesterlund (2011) find that, reviewing the literature, risk preferences do not seem to play an important role for tournament entry, Buser (2011) also finds that the Eckel-Grossman lottery measure predicts

4.3 Can competitiveness account for gender differences in study profile choices?

The students in our sample represent a classical situation. Boys and girls agree on which academic profiles are the most prestigious and provide the highest rewards. Furthermore, profile choices are correlated with the future careers of students. The profile choices of boys and girls correlate with grades as well as with views on how difficult math is. In addition, boys and girls do not differ in math grades, and if anything, girls have slightly higher GPA's than boys. Despite these facts, girls are significantly less likely to choose the prestigious NT profile, and, in turn, significantly more likely to choose the least prestigious profile, CS. Gender differences in study profile choices remain significant when controlling for academic performance as well as mathematical prowess.

The students in our sample also exhibit the standard gender gap in competitiveness. In this section we assess whether gender differences in competitiveness can help account for the gender gap in profile choice. This would show that competitiveness correlates with important decisions outside of the laboratory, and more importantly, that competitiveness is an important psychological attribute that can help account for gender differences in educational choices and as such labor market outcomes.[27]

To use the decision to enter competitions as an attribute, we compute a continuous measure of competitiveness. Specifically, we run a linear regression of the decision to enter the tournament in Round 3 on the Round 2 tournament performance (Tournament), the increase in performance between the Round 2 tournament performance and the Round 1 piece rate performance (T-P) and the probability of winning the tournament in one's class (WinProb), see equation below.

$$Choice_i = \alpha_1 Tournament_i + \alpha_2(T_i - P_i) + \alpha_3 WinProb_i + \varepsilon_i$$

We then assign each subject i the residual ε_i and call that the subject's competitiveness measure. For all subjects it is true that $-1 \leq \varepsilon_i \leq 1$. Furthermore, for all 362 subjects but one is $\varepsilon_i > 0$ if and only if the subject chose to enter the tournament in Round 3. Competitiveness measures how much more likely a subject is to enter a competition, given his or her performances, compared to all other subjects. Hence, a subject who enters the tournament with a high score, has a relatively lower estimated competitiveness than a subject that entered the tournament while having a low performance score. In addition, this measure is also not correlated with the performance and chance of winning of the participant, and as such is a more suitable measure of competitiveness. This will be important when we use this measure as a regressor in academic profile choice, since we want competitiveness to not merely be another measure of (academic) ability.

In Figure 1, we show for each profile choice the mean competitiveness of boys and girls who chose that profile. We add the mean overall tournament entry 0.34 in the figure, so that all numbers are positive. Figure 1 shows that for both boys and girls the students that enter the NT track are the

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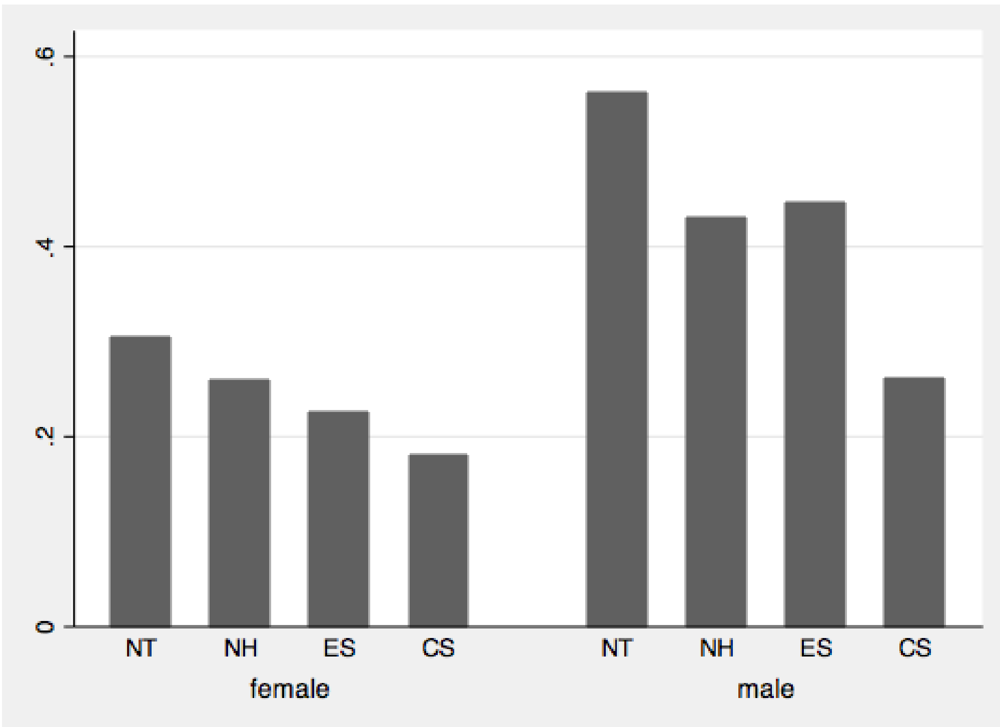
tournament entry and Dohmen and Falk (2011) find the same for the questionnaire measure.

[27]It can of course be that competitiveness correlates with other variables such as mothers' education, etc. We are, however, not aware of any study relating variables different than performance to competitiveness. We are also not aware of studies showing that gender differences in study profile choice after controlling for academic performance can to a large extent be explained by socio-economic variables.

most competitive students, while those that enter the CS track are the least competitive ones. This ranking is even more pronounced among boys with the only difference between boys and girls being that boys who choose ES are slightly more comeptitive than those who choose NH. This indicates that competitiveness as measured by tournament entry may help account for the gender differences in study profile choice.

Figure 1. Compete by gender and profile (conditional on absolute and relative performance)



We start with an intuitive way of investigating whether gender differences in competitiveness can help explain the gender difference in profile choice. We classify a student as competitive, when their $\varepsilon_i > 0$, which coincides with a choice of entering the tournament. We compare the impact of gender on profile choice for different subpopulations by gender and tournament entry. For example, if the gender gap in profile choice is unrelated to competitiveness, the impact of gender on profile choice should be the same for the subsample made up of competitive boys (Comp B) and non-competitive girls (N-comp G) as for the subsample made up of non-competitive boys and competitive girls.

This idea is explored in Table 7 which reports coefficients of regressions of profile choice on a female dummy for subsamples split by gender and competitiveness. The top part of Table 7 has OLS and ordered probit estimations that rank profiles NT<NH<ES<CS and where NT is a choice of 1, and CS a choice of 4. The table shows that the gender gap in profile choice, which is significant for the whole sample, varies strongly with competitiveness. Specifically, the gender gap in profile choice increases with the competitiveness of boys and decreases with the competitiveness of girls.The OLS regression in column (1) provides some intuition for the magnitude of the effect. Overall, girls choose a 0.27 less prestigious profile than boys. Among the subsample that consists of competitive boys and

Table 7. Gender effects by subsample

	(1) OLS	(2) Ordered probit	N
(1) Comp B & n-comp. G	0.54***	0.64***	230
(2) Comp. B & comp. G	0.41**	0.50**	129
(3) N-comp. B & n-comp. G	0.12	0.14	233
(4) N-comp. B & comp. G	-0.01	0.01	132
(5) Whole sample	0.27***	0.32***	
P-value (1) vs (4)	0.02	0.01	

Probit (marginal effects)	(1) NT vs rest	(2) N vs S	(3) CS vs rest
(1) Comp B & n-comp. G	-0.33***	-0.09	0.12***
(2) Comp. B & comp. G	-0.30***	-0.00	0.11**
(3) N-comp. B & n-comp. G	-0.15***	0.05	0.02
(4) N-comp. B & comp. G	-0.12	0.14	0.01
(5) Whole sample	-0.23***	0.00	0.07**
P-value (1) vs (4)	0.06	0.05	0.06

Coefficients are from regressions of profile choice on a female dummy only; standard errors in parentheses; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$; p-values are from post-estimation tests of equality of the female coefficient using Stata 11's suest command.

non-competitive girls, the gender difference is twice as large; a regression of profile choice on gender yields a female coefficient of 0.54. That is, noncompetitive girls choose a 0.54 less prestigious track than competitive boys. As we move to competitive girls, or to non-competitive boys the gender gap shrinks. Finally, focusing on the subsample of non-competitive boys and competitive girls, the gender gap disappears, and girls now pick a 0.01 more prestigious track than boys. The change in the gender dummy between the group of competitive boys and non-competitive girls and the other way round is significant. The results are basically the same when we use ordered probit regression in column (2).

The probit models in the lower part of Table 7 give a more detailed view on this result. We first consider the probability to choose either the most prestigious profile (NT) compared to any other study profile. When we consider only competitive boys and non-competitive girls, girls are 33 percentage points less likely to choose NT. When instead we consider competitive girls and non-competitive boys, girls are only 12 percentage points less likely to choose the NT profile, and in fact, there is no significant gender difference. Furthermore, the gender difference in choices is significantly smaller when we consider competitive girls and non-competitive boys than when we consider competitive boys and non-competitive girls. The results are similar when we either consider choices between the Nature and the Society profiles (the top two versus the bottom two), or when we consider the option to choose CS, the least prestigious profile, compared to any other profile. In all cases the results are very similar. Gender differences are reduced when we reduce the competitiveness of boys and increase the competitiveness of girls.

These results show that gender differences in profile choice are strongly related to gender difference in competitiveness. We now turn to detailed regressions to confirm that the impact of competitiveness on profile choice is robust when controlling for academic performance, where we consider both actual and perceived ability. Furthermore, we aim to assess what part of the gender difference in profile choice can be attributed to gender differences in competitiveness.

Table 8 shows ordered probit regressions on the ranked profile choice. Column (1) recalls the result that the female coefficient is 0.342 (with an s.e. of 0.114). Adding competitiveness as an additional control in column (2) significantly reduces the coefficient by 23 percent to 0.264 (s.e. 0.118). This reduction is significant at p = 0.01.[28] The reduction in the female coefficient on profile choice is driven by competitiveness significantly pushing students into more prestigious profiles, the coefficient on competitiveness is -0.355 (s.e. 0.129). Over the following columns, we add controls for real and perceived ability, beliefs and risk preferences. The competitiveness measure is robust and stays significant throughout.

Pairwise comparisons between Columns (3) and (4), (5) and (6), and so on confirm that competitiveness explains a substantial part of the gender gap in profile choice no matter which controls we include. The change in the gender coefficient upon inclusion of our competitiveness measure is significant for all specifications. When including the full set of controls in columns (13) and (14), the reduction in the gender coefficient is 26 percent. This confirms that competitiveness explains a substantial part of the gender gap in profile choice.

As a robustness check, in the appendix we report ordered probit regressions for our alternative definitions of profile choice. Table 11 shows that the results hold when treating all NH/NT-combi students as NT students and all ES/CS-combi students as ES students and dropping those students for whom we do not know the final choice. Tournament entry significantly affects the level of the chosen profile and explains a significant part of the gender gap in profile choice in all specifications. As a further robustness check, we treat the two combi profiles as separate choices. Table 12 shows that results again carry over. Our competitiveness measure is significant and also significantly affects the gender gap in all specifications.

4.4 The effect of psychological attributes on gender differences in study profile choices

We have seen that about 25 percent of gender differences in competitiveness, that is differences in tournament entry, controlling for performance, can be attributed to gender differences in confidence. An additional 7 percent to gender differences in risk attitudes. We have also seen that confidence is a significant predictor of competitiveness and explains a sizable part of the gender gap in competitiveness. We therefore, in an additional analysis, decompose the competitiveness measure into a measure of pure competitive attitudes, which we call *netcompete*, a measure of confidence and a measure of risk attitudes.

Specifically, to obtain the measure of competitive attitudes, we run the linear regression where, in addition to the controlling for variables used for the competitiveness measure we also control

[28] The test is performed using Stata 11's suest ("seemingly unrelated estimation") command.

Table 8. Profile choice: ordered probit regression

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
Female	0.342***	0.264**	0.449***	0.390***	0.445***	0.399***	0.419***	0.372***	0.445***	0.394***	0.204*	0.141	0.313**	0.265**
	(0.114)	(0.118)	(0.121)	(0.124)	(0.124)	(0.126)	(0.124)	(0.126)	(0.124)	(0.125)	(0.117)	(0.123)	(0.129)	(0.130)
Competitive		-0.355***		-0.319**		-0.338**		-0.295**		-0.341**		-0.299**		-0.407***
		(0.129)		(0.131)		(0.134)		(0.133)		(0.135)		(0.130)		(0.141)
Math grade			-0.188	-0.162	-0.187	-0.167	-0.199	-0.172	-0.188	-0.160			-0.033	-0.000
			(0.133)	(0.133)	(0.134)	(0.133)	(0.135)	(0.134)	(0.133)	(0.133)			(0.143)	(0.141)
GPA			-0.360***	-0.396***	-0.360***	-0.398***	-0.354***	-0.389***	-0.361***	-0.396***			-0.311***	-0.354***
			(0.105)	(0.104)	(0.105)	(0.104)	(0.105)	(0.104)	(0.105)	(0.104)			(0.110)	(0.109)
Rel Math grade			0.509	0.502	0.507	0.508	0.486	0.485	0.512	0.494			0.297	0.290
			(0.475)	(0.475)	(0.475)	(0.475)	(0.478)	(0.478)	(0.475)	(0.474)			(0.487)	(0.484)
Beliefs					0.010	-0.034							-0.053	-0.093
					(0.065)	(0.067)							(0.069)	(0.071)
Lottery choice							-0.062	-0.045					-0.098*	-0.092*
							(0.048)	(0.048)					(0.055)	(0.055)
Risk									-0.008	0.016			0.031	0.053
									(0.032)	(0.033)			(0.036)	(0.036)
Math quartile											0.362***	0.366***	0.346***	0.357***
											(0.078)	(0.078)	(0.076)	(0.077)
Math difficulty											0.122***	0.119***	0.082**	0.083**
											(0.027)	(0.027)	(0.033)	(0.033)
Cut 1	-0.404	-0.574	-3.957	-4.185	-3.925	-4.307	-4.216	-4.355	-4.020	-4.083	0.643	0.497	-2.008	-2.174
Cut 2	0.251	0.089	-3.205	-3.427	-3.173	-3.549	-3.463	-3.597	-3.268	-3.324	1.435	1.295	-1.185	-1.339
Cut 3	1.367	1.216	-1.961	-2.171	-1.928	-2.293	-2.213	-2.338	-2.023	-2.068	2.731	2.601	0.164	0.026
P-value	0.01		0.03		0.04		0.06		0.04		0.04		0.06	
Observations	362	362	362	362	362	362	362	362	362	362	362	362	362	362

Note: Coefficients are from ordered probit regressions; standard errors in parentheses; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$; p-value is from test for equality of gender coefficient using Stata 11's suest command

for confidence and risk preferences (as measured by the lottery choice and the risk question), see equation below:

$$Choice_i = \beta_1 Tournament_i + \beta_2(T_i - P_i) + \beta_3 WinProb_i + \beta_4 Belief_i + \beta_5 Lottery_i + \beta_6 Risk_i + \pi_i$$

We then assign each subject i the residual π_i and call that the subject's competitive attitude.

To have a measure of confidence which is not simply another measure of performance, we run a linear regression of the belief about the relative performance in the Round 2 Tournament on the Round 2 Tournament performance (Tournament), the increase in performance between the Round 2 tournament performance and the Round 1 piece rate performance (T-P) and the probability of winning the tournament in one's class (WinProb), see equation below.

$$Belief_i = \gamma_1 Tournament_i + \gamma_2(T_i - P_i) + \gamma_3 WinProb_i + \varphi_i$$

We then assign each subject i the residual φ_i and call that the subject's confidence.

In Table 9, we report ordered probit regressions of profile choice on netcompete, confidence and risk attitudes. Adding these variables first separately in columns (2) to (4) and then in various combinations in columns (5) to (8), it becomes apparent that around half of the 25% reduction in the gender coefficient upon controlling for competitiveness is due to gender differences in "pure" competitiveness and half to gender differences in confidence. Risk attitudes play only a minor role. In columns (9) to (13), we control for real and perceived ability. Interestingly, the effect of pure competitiveness is not at all affected while the effect of confidence drops to zero. The same is true for the effects of competitiveness and confidence on the gender gap. This indicates that the effect of competitiveness on the gender gap in profile choice conditional on real and perceived ability is due almost entirely to gender differences in pure competitiveness and not to gender differences in confidence or risk aversion.

5 Conclusion

This is the first study that examines whether experimentally measured gender differences in competitiveness can account for gender differences in career choices. We analyzed the first important career choice that young people in the Netherlands make and for which we observe substantial gender differences. At the end of the third year, students in the pre-university track choose between four study profile which are ranked according to difficulty and prestige in the following order: a science-oriented profile (NT), a health-oriented profile (NH), a social science-oriented profile (ES) and a humanities-oriented profile (CS). While 40 percent of the boys (in our data) choose the challenging NT profile, only 17 percent of the girls do so, and while 36 percent of the girls choose the NH profile, only 12 percent of the boys do so. Girls are also more likely to choose CS, the least demanding and prestigious of the profiles.

Ordered probit regressions confirm that girls on average pick a significantly lower ranked profile.

Table 9. Profile choice: ordered probit regression

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
Female	0.342***	0.304***	0.297***	0.329***	0.255**	0.290**	0.285**	0.242**	0.329***	0.290**	0.341***	0.299**	0.264**
	(0.114)	(0.115)	(0.115)	(0.118)	(0.117)	(0.119)	(0.119)	(0.120)	(0.123)	(0.125)	(0.123)	(0.128)	(0.129)
Netcompete		-0.330**			-0.345**	-0.333**		-0.348**		-0.414***			-0.415***
		(0.147)			(0.146)	(0.147)		(0.146)		(0.150)			(0.151)
Confidence			0.144*		0.153*		0.159*	0.167**			-0.046		-0.027
			(0.079)		(0.078)		(0.082)	(0.081)			(0.083)		(0.085)
Lottery choice				-0.079		-0.081	-0.082	-0.084*				-0.097*	-0.099*
				(0.050)		(0.050)	(0.050)	(0.050)				(0.054)	(0.054)
Risk				0.040		0.039	0.052	0.051				0.038	0.034
				(0.035)		(0.035)	(0.035)	(0.035)				(0.035)	(0.036)
Math grade									-0.016	0.016	-0.020	-0.026	0.004
									(0.141)	(0.139)	(0.142)	(0.143)	(0.141)
GPA									-0.326***	-0.362***	-0.322***	-0.310***	-0.345***
									(0.109)	(0.108)	(0.110)	(0.109)	(0.110)
Rel Math grade									0.345	0.356	0.357	0.286	0.305
									(0.484)	(0.480)	(0.483)	(0.488)	(0.482)
Math quartile									0.336***	0.352***	0.340***	0.341***	0.361***
									(0.075)	(0.076)	(0.076)	(0.076)	(0.077)
Math difficulty									0.076**	0.077**	0.077**	0.081**	0.081**
									(0.031)	(0.031)	(0.031)	(0.032)	(0.032)
Observations	362	362	362	362	362	362	362	362	362	362	362	362	362

Note: Coefficients are from ordered probit regressions; standard errors in parentheses; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$; p-value is from test for equality of gender coefficient using Stata 11's suest command

This is despite the fact that the girls in our sample have a significantly higher GPA than the boys. Prior to the moment that these students made their final choice (and were subsequently exposed to different subjects), we administered an experiment to elicit their competitiveness.

Like previous studies, we find that boys are more competitive than girls. This also holds when we control for differences in risk attitudes, (perceived) performance and (perceived) ability. We also find that competitiveness varies strongly and significantly across profiles with students picking better ranked profiles being more competitive. Ordered probit regressions confirm that competitiveness strongly affects profile choice and that this effect is robust to the inclusion of controls for risk preferences and ability. Moreover, our simple measure of competitiveness can explain up to 25 percent of the gender difference in profile choice.

Since the publication of Niederle and Vesterlund (2007)'s results on gender differences in competitiveness, it has often been suggested that these differences may be an important factor explaining gender differences in labor market outcomes. We are the first to formally test this and our results lend support to the extrapolation.

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Appendix

Table 10. Gender and profile choice (alternative specifications)

	(1)	(2)	(3)	(4)	(5)	(6)
	NH/NT as NT and ES/CS and ES			NH/NT and ES/CS as separate profiles		
Female	0.275**	0.331***	0.219*	0.433***	0.494***	0.380***
	(0.121)	(0.126)	(0.130)	(0.115)	(0.118)	(0.121)
Math Grade		-0.181	-0.031		-0.036	0.124
		(0.145)	(0.152)		(0.127)	(0.134)
GPA		-0.383***	-0.357***		-0.319***	-0.284***
		(0.107)	(0.111)		(0.103)	(0.106)
Rel. Math Gr.		0.402	0.226		0.869*	0.692
		(0.494)	(0.499)		(0.462)	(0.466)
Math Difficulty			0.354***			0.360***
			(0.082)			(0.078)
Math Quartile			0.058*			0.068**
			(0.032)			(0.031)
Cut 1	-0.098	-3.818	-1.828	-0.568	-2.759	-0.643
Cut 2	0.281	-3.386	-1.358	-0.006	-2.149	0.015
Cut 3	1.475	-2.089	0.033	0.372	-1.723	0.477
Cut 4				1.299	-0.711	1.576
Cut 5				1.571	-0.429	1.874
Observations	342	342	342	342	342	342

Dependent variable: Profile choice; coefficients are from ordered probit regressions; standard errors in parentheses; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 11. Profile choice: ordered probit regression (treating NH/NT-combi students as NT students)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
Female	0.275**	0.206*	0.331***	0.274**	0.312**	0.272**	0.315**	0.268**	0.340***	0.288**	0.115	0.065	0.212	0.170
	(0.121)	(0.125)	(0.126)	(0.129)	(0.130)	(0.132)	(0.129)	(0.132)	(0.129)	(0.130)	(0.125)	(0.131)	(0.136)	(0.137)
Competitive		-0.322**		-0.307**		-0.303**		-0.299**		-0.361**		-0.256*		-0.386**
		(0.136)		(0.137)		(0.143)		(0.138)		(0.144)		(0.138)		(0.155)
Math grade			-0.181	-0.159	-0.171	-0.158	-0.189	-0.163	-0.180	-0.152			-0.033	-0.007
			(0.145)	(0.145)	(0.146)	(0.146)	(0.147)	(0.146)	(0.144)	(0.144)			(0.153)	(0.152)
GPA			-0.383***	-0.416***	-0.384***	-0.416***	-0.380***	-0.413***	-0.382***	-0.418***			-0.343***	-0.381***
			(0.107)	(0.106)	(0.107)	(0.106)	(0.108)	(0.107)	(0.107)	(0.106)			(0.112)	(0.113)
Rel Math grade			0.402	0.395	0.395	0.394	0.381	0.385	0.398	0.383			0.155	0.153
			(0.494)	(0.497)	(0.495)	(0.497)	(0.497)	(0.498)	(0.492)	(0.492)			(0.500)	(0.498)
Beliefs					0.048	0.006							0.003	-0.038
					(0.071)	(0.074)							(0.076)	(0.078)
Lottery choice							-0.032	-0.015					-0.069	-0.063
							(0.051)	(0.052)					(0.057)	(0.057)
Risk									0.016	0.041			0.058	0.078**
									(0.034)	(0.036)			(0.038)	(0.039)
Math quartile											0.378***	0.378***	0.359***	0.365***
											(0.084)	(0.085)	(0.083)	(0.084)
Math difficulty											0.101***	0.098***	0.065*	0.066**
											(0.028)	(0.028)	(0.033)	(0.033)
Cut 1	-0.098	-0.249	-3.818	-4.036	-3.659	-4.008	-3.961	-4.099	-3.698	-3.764	0.930	0.804	-1.605	-1.785
Cut 2	0.281	0.133	-3.386	-3.602	-3.227	-3.574	-3.529	-3.665	-3.266	-3.328	1.381	1.257	-1.131	-1.306
Cut 3	1.475	1.340	-2.089	-2.291	-1.929	-2.264	-2.230	-2.354	-1.970	-2.018	2.732	2.618	0.264	0.106
P-value	0.03		0.04		0.08		0.07		0.04		0.09		0.10	
Observations	342	342	342	342	342	342	342	342	342	342	342	342	342	342

Note: Coefficients are from ordered probit regressions; standard errors in parentheses; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$; p-value is from test for equality of gender coefficient using Stata 11's suest command

Table 12. Profile choice: ordered probit regression (treating NH/NT and ES/CS-combi as separate choices)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
Female	0.433***	0.365***	0.494***	0.440***	0.479***	0.440***	0.464***	0.422***	0.497***	0.450***	0.289**	0.238*	0.359***	0.320**
	(0.115)	(0.118)	(0.118)	(0.121)	(0.121)	(0.123)	(0.120)	(0.123)	(0.120)	(0.122)	(0.117)	(0.122)	(0.125)	(0.127)
Competitive		-0.324**		-0.301**		-0.301**		-0.279**		-0.339**		-0.257**		-0.370***
		(0.126)		(0.126)		(0.129)		(0.127)		(0.132)		(0.126)		(0.139)
Math grade			-0.036	-0.009	-0.027	-0.009	-0.048	-0.020	-0.036	-0.005			0.112	0.141
			(0.127)	(0.127)	(0.128)	(0.128)	(0.127)	(0.127)	(0.127)	(0.126)			(0.134)	(0.132)
GPA			-0.319***	-0.351***	-0.320***	-0.351***	-0.313***	-0.344***	-0.319***	-0.353***			-0.267**	-0.304***
			(0.103)	(0.101)	(0.103)	(0.101)	(0.103)	(0.101)	(0.103)	(0.101)			(0.107)	(0.106)
Rel Math grade			0.869*	0.873*	0.863*	0.873*	0.840*	0.851*	0.867*	0.859*			0.607	0.609
			(0.462)	(0.464)	(0.463)	(0.464)	(0.463)	(0.464)	(0.462)	(0.462)			(0.468)	(0.467)
Beliefs					0.041	0.001							-0.012	-0.050
					(0.067)	(0.069)							(0.071)	(0.072)
Lottery choice							-0.060	-0.045					-0.100*	-0.096*
							(0.046)	(0.047)					(0.053)	(0.054)
Risk									0.005	0.029			0.053	0.073**
									(0.030)	(0.032)			(0.035)	(0.036)
Math quartile											0.379***	0.380***	0.366***	0.373***
											(0.080)	(0.080)	(0.078)	(0.079)
Math difficulty											0.096***	0.093***	0.075**	0.076**
											(0.026)	(0.027)	(0.032)	(0.032)
Cut 1	-0.568	-0.723	-2.759	-2.941	-2.620	-2.935	-3.013	-3.119	-2.723	-2.764	0.365	0.237	-0.634	-0.787
Cut 2	-0.006	-0.159	-2.149	-2.329	-2.010	-2.323	-2.403	-2.508	-2.113	-2.151	1.014	0.887	0.027	-0.122
Cut 3	0.372	0.222	-1.723	-1.901	-1.584	-1.896	-1.978	-2.081	-1.687	-1.722	1.463	1.337	0.493	0.349
Cut 4	1.299	1.161	-0.711	-0.878	-0.571	-0.872	-0.960	-1.053	-0.675	-0.697	2.530	2.412	1.605	1.476
Cut 5	1.571	1.438	-0.429	-0.590	-0.287	-0.584	-0.674	-0.763	-0.392	-0.409	2.820	2.707	1.907	1.784
P-value	0.02		0.03		0.06		0.06		0.04		0.07		0.08	
Observations	342	342	342	342	342	342	342	342	342	342	342	342	342	342

Note: Coefficients are from ordered probit regressions; standard errors in parentheses; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$; p-value is from test for equality of gender coefficient using Stata 11's suest command