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Chapter 5

Gender, Competition and Career Choices[1]

5.1 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 (see Croson and Gneezy, 2009), the direct evidence linking the experimental literature to outcomes in the education and labor market has been rather scant.[2] This paper aims to close that gap and contributes to both these literatures. Specifically, we investigate to what extent one of the most robust gender differences in laboratory experiments, the gender difference in competitive attitudes, can help account for gender differences in educational choices. We do this by measuring competitiveness among school children for whom we also have educational outcomes such as grades, and linking this data to subsequent educational choices.

Though gender differences in educational choices are smaller than they used to be, they remain significant. While in the U.S. girls take on average as many advanced math and science classes as boys and perform on average at similar levels (Goldin et al., 2006) this is not the case in all OECD countries.[3] Even in the U.S., girls are underrepresented among extremely high achieving

[1]The research in this chapter is joint work with Muriel Niederle and Hessel Oosterbeek.

[2]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."

[3]We will show that in the Netherlands boys are significantly more likely to take math classes in high school

math students. Ellison and Swanson (2010) provide compelling evidence that this gender gap is not driven solely by differences in mathematical ability. Specifically, they show that 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. At the college level, even in the U.S. women are significantly less likely to graduate from a so-called STEM (science, technology, engineering and mathematics) major than men.[4] Research investigating career choices of women and men suggests that among equally gifted students, males are much more likely to choose a math heavy college major (see LeFevre et al., 1992; Weinberger, 2005).

The reason to be concerned about gender differences in math and sciences, compared to, say, literature, is that the choices of math and science classes are most predictive of college attendance and completion (Goldin et al., 2006). Furthermore, performance in mathematics has consistently been found to serve as a predictor for future earnings. For example, Paglin and Rufolo (1990) report that a large fraction of the gender gap in average starting salaries for college graduates is between rather than within detailed college majors (for additional evidence and discussion see Grogger and Eide, 1995; Brown and Corcoran, 1997; Weinberger, 1999; Weinberger, 2001; Murnane et al., 2000; Altonji and Blank, 1999).[5]

To assess the effects of psychological attributes on educational choices, we want to measure them before students make choices which result in different educational experiences. This ensures that measured psychological attributes are not contaminated by the different environments children experience after having selected into different educational careers. We run our study in the Netherlands where, at the end of the third year of secondary school, students in the pre-university track have to choose between four study profiles: a science-oriented profile, a health-oriented profile, a social science-oriented profile and a humanities-oriented profile.[6] There is a clear ranking of these profiles in terms of academic prestige, with the science-oriented profile being the most and the humanities-oriented profile being the least prestigious and challenging. Despite the fact that girls perform slightly better academically, 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

than girls. In France, where like in the Netherlands high school children decide on which set of classes to enroll in, girls are less likely to choose the math and science heavy options (http://media.enseignementsup-recherche.gouv.fr/file/2010/42/2/filles-garcons-egalite-ecole-a-enseignement-superieur2010_139422.pdf).

[4] http://nces.ed.gov/pubs2009/2009161.pdf

[5] In a study on the gender gap in earnings 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.

[6] In the Netherlands, 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 during high school.

and therefore with future labor market positions and earnings.

We aim to assess to what extent choices of study profiles are driven by psychological attributes, most notably competitiveness, as well as grades and students' beliefs about their own talent at math. We focus on competitiveness because gender difference in competitive attitudes is the largest and most robust gender difference found in experimental studies (see Gneezy et al., 2003, Niederle and Vesterlund (2007) and, for an overview, Niederle and Vesterlund, 2011). In the first paper on gender differences in preferences for performing under competitive or non-competitive incentive schemes, Niederle and Vesterlund (2007) assess choices of college students that perform equally well in a simple arithmetic task. They find that while 73 percent of men choose a competitive tournament payment scheme instead of non-competitive piece-rate compensation, only 35 percent of women do so. Subsequent research has confirmed this gender difference in the willingness to compete in somewhat stereotypical male tasks, such as simple arithmetic problems (see Niederle and Vesterlund, 2011). Sutter and Rützler (2010) provide evidence that these gender differences in competitiveness are present among children of all ages, beginning when they are 3 years old.

Niederle and Vesterlund (2007) show that gender differences in competitiveness are largely due to gender differences in confidence and competitive attitudes, with gender differences in risk aversion playing a minor role. We therefore aim to decompose the effect of competitiveness on educational choices into pure competitive attitudes, as well as confidence and risk, which are other well-studied traits that show significant gender differences (see Croson and Gneezy, 2009).

The fact that women shy away from competition while men compete too much has potentially important implications for labor market outcomes. People who shy away from competitive environments may self-select into different, potentially lower paid, careers. Gender differences in competitive attitudes may therefore be a potential explanation for the under-representation of women in certain fields such as the sciences which are viewed as competitive.[7]

The goal of this paper is to assess the extent to which gender differences in competitiveness can account for gender differences in educational career choices. Among a set of four schools in and around Amsterdam, we administered an experiment just prior to the moment when students make their first important educational choice. We elicit the students' competitiveness using the design of Niederle and Vesterlund (2007), as well as their confidence and risk aversion. We also assess the students' beliefs about their mathematical prowess, as grades may not be the most accurate predictor of mathematical ability. The school provided us with the subsequent profile choices of

[7] The fact that women shy away from competition more than men may also account for the fact that few qualified women reach the top. Women only account for 2.5 percent of the five highest paid executives among a large dataset of U.S. firms (see Bertrand and Hallock, 2001). Furthermore, it may account for why the gender log wage gap accelerates in the upper tail, as documented by Albrecht et al. (2003) for Sweden, and later confirmed in other studies Arulampalam et al. (e.g. 2007).

students as well as their grades.

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. 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 20 percent of the gender difference in profile choice.

The remainder of this paper is organized as follows. Section 5.2 provides details of the structure of Dutch secondary education and of the study profiles. Section 5.3 discusses the design of our study and describes the data. Section 5.4 presents and discusses the results. Section 5.5 summarizes and concludes.

5.2 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 vocational track.[8] Around 20 percent of students graduate from the pre-university track, 25 percent from the general track and the remaining 55 percent from 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 (optionally) world orientation. It supposedly measures students' cognitive ability. Our sampling frame consists of the 20 percent pre-university track students.[9]

Halfway through the six years of secondary school, at the end of grade 9, students in the pre-university track have to choose between 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 5.1 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.[10] Mathematics is

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

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

[10]In addition the students take the following non-profile specific subjects: Dutch (480 hours), English (400), second

Table 5.1: 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.

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 NT/NH and ES/CS. In the NT/NH profile, students take the hardest mathematics version, Mathematics B, albeit only at 520 hours. Furthermore, Physics is not required. In the ES/CS profile, students replace one of the CS-electives with the economics course. As such, the combined profiles are in between the pure profiles, though a little closer to NT and ES, respectively.

The choice of study profile in secondary school is strongly correlated with the choice of major in tertiary education.[11] Table 5.2 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.[12] Different study profiles are not only associated with different careers, they also differ in the

foreign language, Latin or Greek (480), social studies (120), general natural sciences (120), culture (160), and sports (160). The students spend roughly half their time on profile specific subjects and half on common subjects.

[11]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 take major-relevant courses.

[12]Some studies actually restrict entry to students who took certain profiles or courses within profiles. For example,

Table 5.2: 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.

likelihood 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.

In year three of the pre-university track, at the end of which students decide upon their study profile, girls perform overall somewhat better than boys. They are, for instance, less likely to drop out or repeat a year. In standardised tests such as the PISA test[13], girls and boys perform similarly whereby boys do slightly better at math and girls slightly better at other subjects (Driessen and Van Langen, 2010).

Despite these similarities between boys and girls, they make very different study profile choices. 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.[14]

medical schools require NT or NH; to study math, having taken Math B in high school is required.

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

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

5.3 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. To achieve this, we focus on a small set of students in the Netherlands who are about to choose their study profile. We assess their psychological attributes through a classroom experiment. In addition we collected information through a short questionnaire and received administrative data provided by the schools. This will allow us to study the effect of psychological attributes after controlling for classic channels that may account for profile choices, such as the students' grades. In this section we describe the environment and the participants in our study, followed by the experimental design for assessing the psychological traits.

5.3.1 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.[15] For 20 of these students, we use the profile choice from the questionnaire.[16] 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 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.

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

[16]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.

5.3.2 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 non-competitive 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 that 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 the 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, at which time they could make inferences about their relative performance. 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 would be 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 between the two payment schemes. In case round three was selected for payment, the earnings were computed as follows. 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 a participant's choice did not affect the payoffs of any other participant.[17]

We elicit two additional psychological attributes that may affect the decision to enter the tournament as well as the decision to choose a prestigious study profile in high school. The first is confidence, measured by the beliefs of participants about their relative performance. Gender differences in beliefs about relative performance, especially in performances in tournaments, are well documented and have been shown to explain a portion of the gender gap in tournament entry (see Niederle and Vesterlund (2007) and also Mobius et al., 2011). Gender differences in confidence may also influence the profile choices of students. We therefore elicited the students' beliefs about their relative performance after round 3. 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.[18]

The final factor that may influence the choice of compensation scheme and academic careers is attitudes towards risk. While risk attitudes are correlated with tournament entry (see for example Buser, 2011), note that the literature so far has failed to find that risk attitudes play a prominent role in accounting for gender differences in the choice of compensation schemes (see Niederle and Vesterlund, 2011). 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 was 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 advantages and disadvantages. First, it is simply a survey question, which makes it cheap, but potentially less reliable. 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 more stable over time than lottery measures for risk attitudes.

The experiment concluded with a questionnaire. Mathematical ability can be expected to be an

[17] 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 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.

[18] 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.

important factor when choosing academic profiles. It may well be that grades are not a perfect predictor of mathematical ability. We therefore wanted additional measures of mathematical prowess. Specifically, we asked 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%).[19] 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).[20] Finally, we asked students which profile they expected to choose in June, several weeks after the experiment. The experiments were conducted in March, April and May of 2011.

5.4 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. We document significant gender differences in profile choices that are not explained by grades or beliefs about mathematical prowess. Second, we assess gender differences in competitiveness. We analyze the extent to which other psychological attributes such as confidence and risk attitudes can account for gender differences in competitiveness. We find a significant gender difference in competitiveness. About 25 percent of this gap can be attributed to gender differences in confidence, while risk aversion can explain an additional 10-15 percent, leaving a large part of gender differences in tournament entry unaccounted for. In the main results 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 the effects of competitive attitudes, confidence and risk attitudes. The most important and robust psychological attribute is competitiveness.

5.4.1 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

[19] 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.

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

Table 5.3: 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	

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 of subjects who chose that profile. Grades are out of 10 with higher numbers being better grades. Math difficulty goes from 0 - very easy to 10 - very hard. Math quartile goes from 1 - best 25% to 4 - worst 25%. The last column reports p-values from Kruskal-Wallis tests.

to pick the combined profiles. Of the 173 students in those two schools, 64 students choose the NT/NH combination and 18 pick the CS/ES 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. Lastly, as a further robustness check, in the appendix, we show results where we treat NT/NH and ES/CS as separate categories.[21] The results remain qualitatively the same.

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 5.3 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 5.3 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.[22] The picture that emerges is very similar;

[21]For these analyses we have to drop an additional 20 students for whom we do not have a final profile choice. The multiple choice question in the questionnaire did not allow for combined profiles and we do therefore not know whether these students would have picked one of the mixed profiles.

[22]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

Table 5.4: 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	

Grades are out of 10 with higher numbers being better grades. Math difficulty goes from 0 - very easy to 10 - very hard. Math quartile goes from 1 - best 25% to 4 - worst 25%. The last column of the top four rows reports p-values from Wilcoxon ranksum tests and for the profile choice we report the p-value from a Fisher's exact test.

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.[23]

The second part of Table 5.3 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 for just the mathematics grade. Likewise, students that chose 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 5.4. 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 themselves as less likely to be among the high math ability children in their school. This could reflect that girls are truly less able than boys in mathematics, as grades may be a function of true ability, as well as, for example, conscientiousness. On the other hand, the measure on self-assessed mathematical prowess may already include gender differences in confidence, and as such represent already a psychological attribute.

While academically boys and girls are very comparable, girls make significantly different profile

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.

[23] 50% think that NT gives the best salary prospects, 27% think NH, 20% ES and 2% CS.

Table 5.5: 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 (C1)	-0.404	-3.957	-1.766
Cut 2 (C2)	0.251	-3.205	-0.948
Cut 3 (C3)	1.367	-1.961	0.392
Female/(C3-C1)	0.193	0.225	0.152
N	362	362	362

Dependent variable: Profile choice, where NT<NH<ES<CS. Coefficients from ordered probit regressions; standard errors in parentheses; *, ** and *** denote significance at 10, 5 and 1 percent, respectively.

choices compared to boys. The lower part of Table 5.4 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. Note that in our sample, boys and girls are as likely to choose one of the Nature profiles compared to one of the Society profiles. This is not the case in national statistics, where girls are overall more likely to choose a Society profile, while boys are overall more likely to choose a Nature profile.

To more precisely understand gender differences in profile choice, we show in Table 5.5 ordered probit regressions where we order profiles by NT<NH<ES<CS. The first column shows that girls on average choose a significantly less prestigious profile. Specifically, the effect of being female bridges almost 20 percent of the distance between the best and the worst 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.[24] When we include these three academic achievement

[24]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 of students with a better grade. We then normalize the measure by dividing by the number of students in the class.

variables, the gender gap actually increases, and being female bridges almost 23 percent of the distance between the best and the worst profile. Note that the coefficient on female is actually slightly larger than the coefficient on the GPA. An increase in 1 in the GPA, which corresponds to about 144 percent of a standard deviation increase, corresponds to bridging 18 percent of the gap between the best and the worst profile. 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 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 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.[25]

Table 5.10 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. Finally, the results also hold when we use each student's own ranking of his or her chosen profile (i.e. the girls rank the profiles they choose themselves lower than the boys rank their own chosen profiles).

To provide additional insights on the gender differences in profile choice, 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 5.5. That is, the following represent gender differences when controlling for grades and feelings about mathematical prowess. 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 7 (s.e. 0.03) percentage points more likely to choose CS than boys, also a significant difference ($p = 0.03$).

To summarize, boys and girls in our sample have similar grades, though boys are more confident about their mathematical prowess. Boys and girls, however, differ vastly in their study profile choices, with girls choosing significantly less prestigious profiles. This is the case even after controlling for grades and feelings of mathematical prowess. In the next section we assess the

[25] Alternatively, when we use simple OLS regressions, where NT is modeled as a choice of 1 up to CS as a choice of 4. The coefficient on female is 0.296 (s.e. 0.105, $p<0.01$) without any controls. It increases to 0.349 (s.e. 0.099, $p< 0.01$) when we add the controls from Column 2 in Table 5, which is slightly larger than the coefficient on the GPA which is -0.297 (s.e. 0.085, $p<0.01$). When we add all the controls from Column 3 the gender coefficient is 0.225 (s.e. 0.095, $p<0.05$), comparable to the coefficient on the GPA of -0.251 (s.e. 0.083, $p< 0.01$).

psychological attributes of the students in our sample. We will then assess whether these attributes can help account for gender differences in study profile choices.

5.4.2 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 or other psychological attributes at this stage cannot be the result of differences in exposure to, or experiences in different study programs. More specifically, we do not have to worry that any differences between students across chosen study profiles are due to the exposure to different teachers, classmates and so on. We can therefore assess the psychological attributes of students which, in turn, may influence study profile choice.[26]

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).[27] In the round 2 tournament, there is no 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 of winning the round 2 tournament given their performance and the performance of their classmates.[28] 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 the performance in round 2, every student with a chance of winning the tournament of 25 percent and higher has higher expected 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 5.6 shows marginal effects of a probit regression of tournament entry in round 3. Girls have a 26 percentage points lower probability of entering the tournament compared to boys, when controlling for performance in the round 2 tournament, the improvement in performance between

[26]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, such as the chance of winning the tournament, the accuracy of the guessed rank and, just as in the previous section, the relative math grade.

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

[28]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).

Table 5.6: Determinants of tournament entry

	(1)	(2)	(3)	(4)	(5)
Female	-0.261***	-0.191***	-0.166***	-0.153***	-0.142**
	(0.051)	(0.055)	(0.055)	(0.056)	(0.057)
Tournament	0.054***	0.022	0.020	0.024	0.014
	(0.020)	(0.021)	(0.021)	(0.021)	(0.021)
T - PR	-0.028**	-0.022*	-0.018	-0.018	-0.014
	(0.013)	(0.013)	(0.014)	(0.014)	(0.014)
Win Prob	0.231	0.062	0.041	-0.006	0.087
	(0.204)	(0.210)	(0.211)	(0.215)	(0.228)
Guessed rank		-0.292***	-0.293***	-0.274***	-0.269***
		(0.044)	(0.043)	(0.044)	(0.043)
Lottery			0.075***	0.033	0.037
			(0.023)	(0.024)	(0.025)
Risk-taking				0.082***	0.089***
				(0.019)	(0.019)
Math grade					0.142**
					(0.067)
GPA					-0.121*
					(0.063)
Math Relative					0.078
					(0.248)
Math quartile					0.069
					(0.044)
Math hard					-0.009
					(0.016)
N	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 coefficients of a probit regression 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 effects are in parentheses; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$ of the underlying coefficient.

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).

We now turn to the analysis of the two other psychological attributes, confidence and risk aversion. To elicit confidence, we asked students to rank their relative performance in the round 2 tournament from 1 (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, with the two distributions 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.[29] While 56 boys and 21 girls believe they have the highest performance in their group, the numbers would be 46 and 41 if the optimal guessed rank is used. Using the optimal guessed rank, there is no gender difference in optimal beliefs, which average 2.42 for boys and 2.57 for girls (p=0.54, 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 0.500 (s.e. 0.118, p = 0.00).[30] This confirms that girls, given their relative performance, are significantly less confident than boys.

To assess risk attitudes, we use an incentivized risk measure, which has participants choose among lotteries, where 1 is the risk free choice of €2 and 5 is the risky choice to receive €6 with a 50 percent chance.[31] Boys on average pick a significantly riskier lottery, choosing on average 3.46 compared to 2.99 for girls, a significant difference (p = 0.00; t-test). 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).[32]

The two additional psychological measures, confidence and risk aversion, may not only affect the choice of study profiles, but also of tournament entry. In Niederle and Vesterlund (2007) gender

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

[30]The coefficient on the optimal guessed rank is 0.622 (s.e. 0.057, p=0.00).

[31]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.

[32]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.

differences in confidence account for about one third of the gender gap in tournament entry, while gender differences in risk attitudes only play a minor role. In their survey, Niederle and Vesterlund (2011) show that these findings are the norm in the literature. Adding the guessed rank to the probit regression on tournament entry in Table 5.6, the gender coefficient drops by about 27 percent and is now 19 percentage points and still very significant. Adding the lottery and questionnaire measures of risk to performances and beliefs on relative performance reduces the gender gap in tournament entry by a further 4 percentage points to 15 percentage points which is a reduction of 15 percent in terms of the initial gender difference (compare Columns 2 and 4). Finally, when we include measures of mathematical ability and overall grades, as well as measures of mathematical prowess, the gender gap in tournament entry is only slightly reduced, leaving a large and significant gender gap in tournament entry of 14 percentage points.

In summary, the students in our sample follow the standard gender differences in the choice of competition (see Niederle and Vesterlund, 2011). Controlling for performance, girls are about 26 percentage points less likely to enter a tournament. Boys have significantly more optimistic views about their relative performance than girls, and this gender difference in confidence accounts for about one quarter of the gender gap in tournament entry. Risk attitudes, measured by a lottery choice and a simple questionnaire item, also significantly predict tournament entry, and account for an additional 15 percent of the original gender gap in tournament entry. A final 5 percent of the original gender gap can be accounted for when controlling for grades and beliefs on mathematical prowess.

5.4.3 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. 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 these 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.

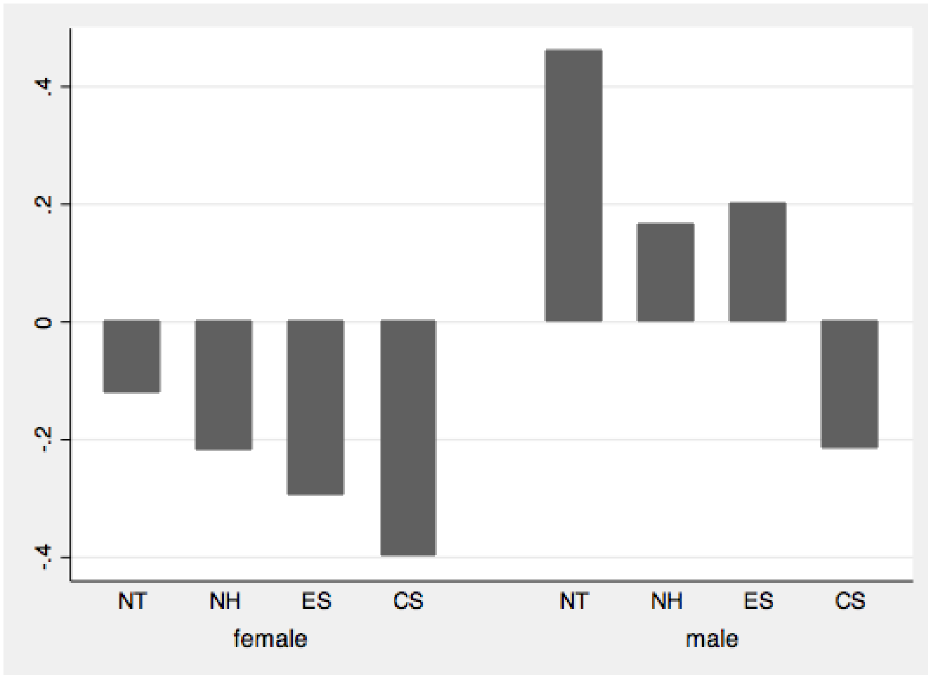
To use the decision to enter competitions as an attribute, we compute a continuous measure of competitiveness. Specifically, we run a linear regression of the decision to enter the tournament in round 3 on the round 2 tournament performance (Tournament), the increase in performance between the round 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, normalize the resulting variable to have variance of one and call this the subject's competitiveness. For all subjects it is the case 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. Recall that tournament entry is higher the higher the performance of subjects in the addition task. Therefore, given our definition of competitiveness, a subject who enters the tournament with a high score has a relatively lower estimated competitiveness than a subject that entered the tournament with a low score. In addition, this measure is not correlated with the performance and chance of winning of the participant, and as such is a more suitable measure of competitiveness than the mere binary tournament entry variable. This is especially relevant when we regress competitiveness on study profile choice, since we do not want competitiveness to merely be another measure of (academic) performance.

In Figure 5.1, we show for each profile choice the mean competitiveness of boys and girls who chose that profile. The figure shows that for both boys and girls the students who enter the NT track are the most competitive students, followed by NH and ES, while those that enter the CS track are the least competitive ones. This ranking is even more pronounced among boys. This indicates that competitiveness as measured by our short classroom experiment may help account for the gender differences in study profile choice.

Figure 5.1: Competitiveness 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 if $\varepsilon_i > 0$, which coincides with 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 5.7 which reports coefficients of regressions of profile choice on a female dummy for subsamples split by gender and competitiveness. The top part of Table 5.7 has ordered probit estimations that rank profiles NT<NH<ES<CS. The table shows that the gender gap in profile choice, which is significant for the whole sample, varies strongly with competitiveness. The gender gap in profile choice increases with the competitiveness of boys and decreases with the competitiveness of girls. When we consider competitive boys and non-competitive girls, then, on its own, gender bridges about 34% of the gap between choosing the best and the worst profile (see Column 2 of Table 5.7). When, on the other hand, we consider non-competitive boys and competitive girls, then there is no gender difference in profile choice at all. The difference in the gender effect between the groups made up of competitive boys and non-competitive girls and the other way round is significant.

Table 5.7: Gender effects by subsample

	(1) Ordered probit	(2) Female/(C3-C1)		N
(1) Comp B & n-comp. G	0.64***	0.34***		230
(2) Comp. B & comp. G	0.50**	0.28**		129
(3) N-comp. B & n-comp. G	0.14	0.08		233
(4) N-comp. B & comp. G	0.01	0.01		132
(5) Whole sample	0.32***	0.19		
P-value (1) vs (4)	0.01			

Probit (marginal effects)	(1) NT vs rest	(2) N vs S	(3) CS vs rest	(4) Best vs rest
(1) Comp B & n-comp. G	-0.33***	-0.09	0.12***	-0.32***
(2) Comp. B & comp. G	-0.30***	-0.00	0.11**	-0.24**
(3) N-comp. B & n-comp. G	-0.15***	0.05	0.02	-0.15**
(4) N-comp. B & comp. G	-0.12	0.14	0.01	-0.07
(5) Whole sample	-0.23***	0.00	0.07**	-0.22***
P-value (1) vs (4)	0.06	0.05	0.06	0.03

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.

The probit models in the lower part of Table 5.7 give a more detailed view on this result. We first consider the probability of choosing 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 choosing NT 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 consider choices between the Nature and the Society profiles (the top two versus the bottom two), or when we consider the probability of choosing CS, the least prestigious profile, compared to any other profile. Finally, we consider a student specific ordering of study profiles. Specifically, for each student we ask whether they pick the profile that they themselves deem to be the one chosen by the best students, or another 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 differences 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

Table 5.8: Profile choice: ordered probit regression

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Female	0.342***	0.265**	0.449***	0.390***	0.204*	0.142	0.329***	0.269**
	(0.114)	(0.119)	(0.121)	(0.126)	(0.117)	(0.125)	(0.123)	(0.131)
Competitive		-0.156***		-0.141**		-0.132**		-0.146**
		(0.058)		(0.060)		(0.059)		(0.061)
Math grade			-0.188	-0.163			-0.016	0.010
			(0.133)	(0.137)			(0.141)	(0.146)
GPA			-0.360***	-0.396***			-0.326***	-0.363***
			(0.105)	(0.107)			(0.109)	(0.111)
Rel Math grade			0.509	0.501			0.345	0.341
			(0.475)	(0.487)			(0.484)	(0.500)
Math quartile					0.362***	0.366***	0.336***	0.342***
					(0.078)	(0.079)	(0.075)	(0.077)
Math difficulty					0.122***	0.119***	0.076**	0.074**
					(0.027)	(0.028)	(0.031)	(0.032)
Cut 1	-0.404	-0.450	-3.957	-4.073	0.643	0.602	-1.766	-1.879
Cut 2	0.251	0.213	-3.205	-3.315	1.435	1.400	-0.948	-1.053
Cut 3	1.367	1.341	-1.961	-2.059	2.731	2.706	0.392	0.299
Female/(C3-C1)	0.193	0.148	0.225	0.194	0.098	0.067	0.152	0.124
Dif.	23.3%		13.8%		31.6%		18.4%	
Bootstrap p-value	0.003		0.009		0.013		0.008	
Observations	362	362	362	362	362	362	362	362

Coefficients are from ordered probit regressions; bootstrap standard errors in parentheses; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

difference in profile choice can be attributed to gender differences in competitiveness.

Table 5.8 shows ordered probit regressions on the ranked profile choice. Column 1 recalls the result that the being female bridges 19.3 percent of the gap between choosing the best and the worst profile. Adding competitiveness as an additional control in Column 2 significantly reduces the effect of being female by 23.3 percent down to 14.8 percent. This reduction is significant at p < 0.01.[33] The reduction in the female coefficient on profile choice is driven by competitiveness significantly pushing students into more prestigious profiles. An increase in competitiveness by one standard deviation bridges 8.7 percent of the gap between choosing the best and worst profile, and corresponds to about 59 percent of the size of the effect of being female. Over the following columns, we add controls for real and perceived ability, separately and jointly. The competitiveness measure is robust and stays significant throughout.

Pairwise comparisons between Columns 3 and 4, 5 and 6, and 7 and 8 confirm that competitiveness explains a substantial part of the gender gap in profile choice no matter which controls we include.

[33] We use bootstrap with 10’000 iterations and count the fraction of differences between Column 2’s and Column 1’s Female/(C3-C1) which are negative or zero.

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 7 and 8, the reduction in the effect of being female is still 18.4 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 5.11 shows that the results hold when treating all NH/NT-combi students as NT students and all ES/CS-combi students as ES students. 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 5.12 shows that results again carry over. Our competitiveness measure is significant and also significantly affects the gender gap in all specifications. As a final robustness check, Table 5.13 shows that the results also hold when we use each student's own ranking of their chosen profile.

Competitiveness, as measured by the decision to enter a tournament in a classroom experiment can account for 18 percent of the gender gap in choices when controlling for grades and feelings of mathematical prowess. This shows the importance of this attribute as a determinant of gender differences in career choice. It also confirms the external validity of the large experimental literature on gender differences in tournament entry in stereotypical male tasks.

5.4.4 Decomposing the effect of competitiveness

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 15 percent to gender differences in risk attitudes. Confidence and risk attitudes can moreover be expected to affect the choice of profile. 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 pure competitive attitudes, we run a linear regression where, in addition to controlling for performances and the chance of winning, we also control for confidence (as measured by the guessed rank) 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. Then, just as in the previous section we normalize the measure such that the variance is one, and call this variable the subject's competitive attitude denoted by *netcompete*.

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 normalize the variable to have a variance of one and call it the subject's confidence. We also multiply the residual by (-1) such that a higher confidence measure is associated with higher confidence for a given performance.

In Figure 2 we plot the average values of competitive attitudes (netcompete), confidence and the two risk attitude measures by profile choice and gender. The figure shows that netcompete is positively correlated with profile quality for both boys and girls which suggests that it is an important variable to account for gender differences in study profile choice. The same is true to a lesser extent for confidence which too might play a role in explaining the gender gap in profile choice. There is less of a clear pattern for risk preferences.

In Table 5.9, 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 percent 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.

5.5 Conclusions

This is the first study that examines whether experimentally measured gender differences in competitiveness can account for gender differences in career choices. We analyze the first important

Figure 5.2: Psychological attributes by gender and profile

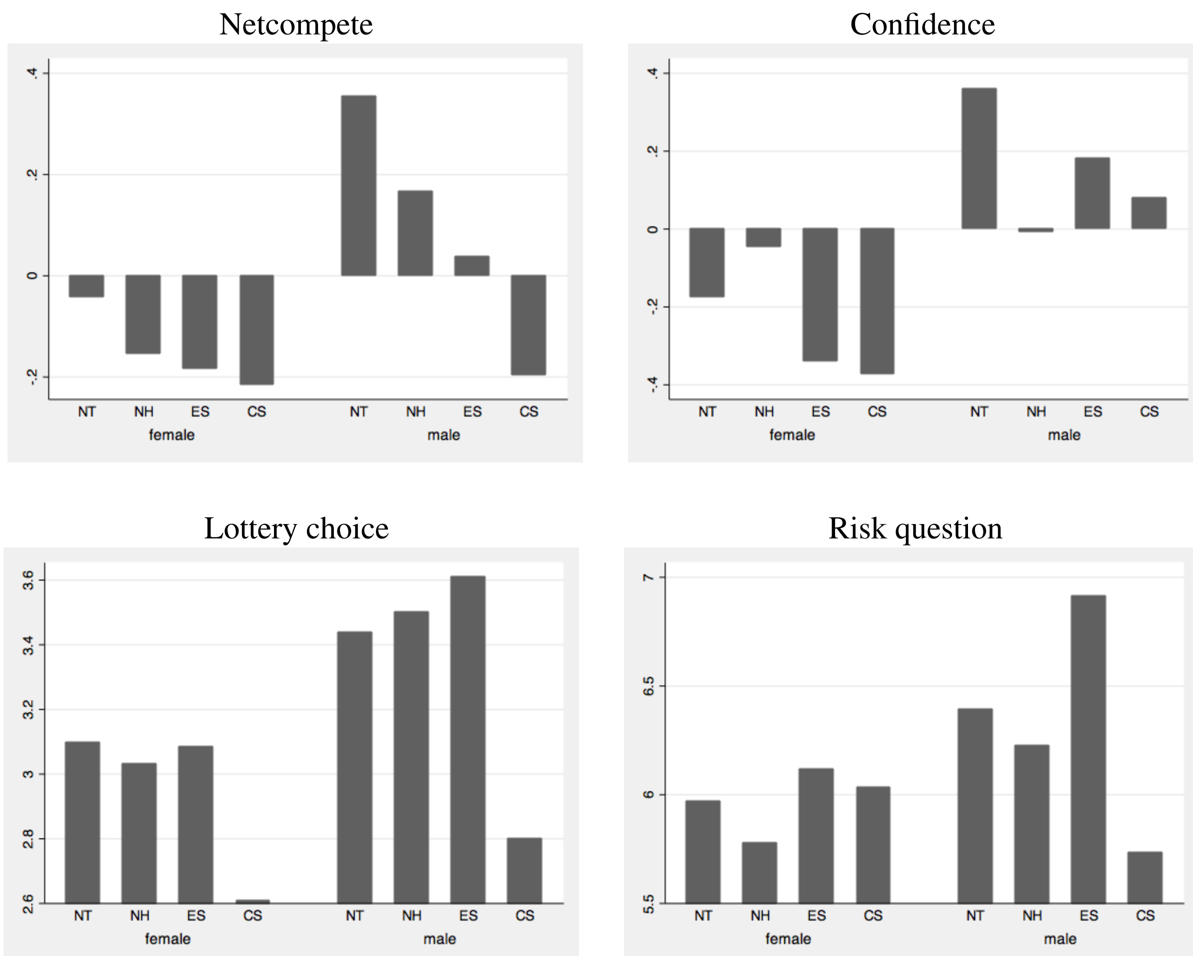


Table 5.9: Profile choice: ordered probit regression

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
Female	0.342***	0.304***	0.298**	0.329***	0.256**	0.289**	0.286**	0.242**	0.329***	0.290**	0.342***	0.299**	0.264**
	(0.114)	(0.117)	(0.117)	(0.119)	(0.119)	(0.121)	(0.121)	(0.123)	(0.123)	(0.129)	(0.126)	(0.131)	(0.133)
Netcompete		-0.129**			-0.134**	-0.130**		-0.135**		-0.161***			-0.162***
		(0.056)			(0.057)	(0.057)		(0.057)		(0.060)			(0.061)
Confidence			0.109*		0.116*		0.120*	0.127**			-0.037		-0.022
			(0.061)		(0.061)		(0.063)	(0.064)			(0.066)		(0.069)
Lottery choice				0.040		0.039	0.051	0.051				0.038	0.034
				(0.036)		(0.036)	(0.036)	(0.037)				(0.037)	(0.038)
Risk				-0.079		-0.081	-0.082	-0.084				-0.097*	-0.099*
				(0.051)		(0.051)	(0.051)	(0.051)				(0.056)	(0.057)
Math grade									-0.016	0.017	-0.020	-0.026	0.004
									(0.141)	(0.145)	(0.147)	(0.149)	(0.148)
GPA									-0.326***	-0.363***	-0.322***	-0.310***	-0.345***
									(0.109)	(0.111)	(0.113)	(0.113)	(0.114)
Rel Math grade									0.345	0.357	0.358	0.286	0.307
									(0.484)	(0.496)	(0.498)	(0.505)	(0.502)
Math quartile									0.336***	0.352***	0.341***	0.341***	0.361***
									(0.075)	(0.077)	(0.078)	(0.078)	(0.080)
Math difficulty									0.076**	0.077**	0.077**	0.081**	0.081**
									(0.031)	(0.032)	(0.033)	(0.033)	(0.034)
Cut 1	-0.404	-0.428	-0.430	-0.417	-0.456	-0.456	-0.384	-0.422	-1.766	-1.790	-1.744	-1.814	-1.862
Cut 2	0.251	0.234	0.229	0.241	0.210	0.208	0.279	0.247	-0.948	-0.959	-0.924	-0.992	-1.027
Cut 3	1.367	1.357	1.351	1.364	1.340	1.340	1.410	1.388	0.392	0.393	0.414	0.357	0.335
f/(c3-c1)	0.193	0.170	0.167	0.185	0.143	0.161	0.159	0.134	0.152	0.133	0.158	0.138	0.120
Dif.		11.9%	13.5%	4.1%	25.9%	16.6%	17.6%	30.6%		12.5%	-3.9%	9.9%	21.1%
Bootstrap p-value	ref.	0.013	0.033	0.296	0.003	0.049	0.061	0.007	ref.	0.011	0.706	0.123	0.044
Observations	362	362	362	362	362	362	362	362	362	362	362	362	362

Coefficients are from ordered probit regressions; bootstrap standard errors in parentheses; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$;

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 of secondary school choose between four study profiles 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 sample choose the challenging NT profile, only 17 percent of the girls do so. Girls, on the other hand, are twice as 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. This is despite the fact that the girls in our sample have a significantly higher GPA than the boys and do no worse at math. Prior to the moment that these students made their final choice (and were subsequently exposed to different academic 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, performance, confidence and (perceived) ability. We also find that competitiveness varies strongly and significantly across chosen 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 grades and perceived talent for math.

Most importantly, our simple measure of competitiveness can explain around 20 percent of the gender difference in profile choice. This result is very robust, as controlling for competitiveness significantly reduces the gender gap in all our specifications.

We show that the gender gap in competitiveness is partially explained by gender differences in confidence and, to a lesser degree, risk attitudes. In a further step, we therefore decompose our measure of competitiveness into measures of pure competitiveness, confidence, and risk attitudes. We show that the effect of competitiveness on the gender gap in profile choice conditional on real and perceived ability is due almost entirely to pure competitiveness.

In summary, we show that gender gap in experimentally measured competitiveness can explain a large and significant part of the gender differences in an important academic career choice in a group of Dutch secondary school students. This demonstrates the external validity of the robust laboratory finding of gender differences in competitiveness.

5.6 Appendix

Table 5.10: Gender and profile choice (alternative specifications)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	NH/NT as NT and ES/CS and ES			NH/NT and ES/CS as separate profiles			Students' own ranking		
Female	0.275^{**}	0.331^{***}	0.219^{*}	0.433^{***}	0.494^{***}	0.380^{***}	0.414^{***}	0.538^{***}	0.460^{***}
	(0.121)	(0.126)	(0.130)	(0.115)	(0.118)	(0.121)	(0.117)	(0.124)	(0.126)
Math Grade		-0.181	-0.031		-0.036	0.124		0.145	0.277^{**}
		(0.145)	(0.152)		(0.127)	(0.134)		(0.124)	(0.130)
GPA		-0.383^{***}	-0.357^{***}		-0.319^{***}	-0.284^{***}		-0.367^{***}	-0.337^{***}
		(0.107)	(0.111)		(0.103)	(0.106)		(0.109)	(0.110)
Rel. Math Gr.		0.402	0.226		0.869^{*}	0.692		1.225^{***}	1.136^{**}
		(0.494)	(0.499)		(0.462)	(0.466)		(0.466)	(0.473)
Math Quartile			0.354^{***}			0.360^{***}			0.150^{*}
			(0.082)			(0.078)			(0.077)
Math Difficulty			0.058^{*}			0.068^{**}			0.070^{**}
			(0.032)			(0.031)			(0.032)
Cut 1	-0.098	-3.818	-1.828	-0.568	-2.759	-0.643	-0.251	-1.330	0.246
Cut 2	0.281	-3.386	-1.358	-0.006	-2.149	0.015	0.578	-0.433	1.171
Cut 3	1.475	-2.089	0.033	0.372	-1.723	0.477	1.505	0.562	2.193
Cut 4				1.299	-0.711	1.576			
Cut 5				1.571	-0.429	1.874			
F/(Cmax-C1)	0.175	0.191	0.118	0.202	0.212	0.151	0.236	0.284	0.236
Observations	342	342	342	342	342	342	354	354	354

Coefficients are from ordered probit regressions; robust standard errors in parentheses; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 5.11: Profile choice: ordered probit regression (treating NH/NT-combi students as NT students)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Female	0.275**	0.206	0.331***	0.274**	0.115	0.065	0.219*	0.168
	(0.121)	(0.126)	(0.126)	(0.132)	(0.125)	(0.134)	(0.130)	(0.139)
Competitive		-0.142**		-0.135**		-0.113*		-0.131**
		(0.061)		(0.062)		(0.063)		(0.065)
Math grade			-0.181	-0.159			-0.031	-0.011
			(0.145)	(0.151)			(0.152)	(0.159)
GPA			-0.383***	-0.415***			-0.357***	-0.388***
			(0.107)	(0.110)			(0.111)	(0.115)
Rel Math grade			0.402	0.395			0.226	0.224
			(0.494)	(0.513)			(0.499)	(0.521)
Math quartile					0.378***	0.378***	0.354***	0.356***
					(0.084)	(0.086)	(0.082)	(0.084)
Math difficulty					0.101***	0.098***	0.058*	0.056*
					(0.028)	(0.029)	(0.032)	(0.033)
Cut 1	-0.098	-0.136	-3.818	-3.929	0.930	0.894	-1.828	-1.942
Cut 2	0.281	0.246	-3.386	-3.495	1.381	1.346	-1.358	-1.470
Cut 3	1.475	1.453	-2.089	-2.184	2.732	2.707	0.033	-0.065
f/(c3-c1)	0.175	0.130	0.191	0.157	0.064	0.036	0.118	0.090
Dif.	25.7%		17.8%		43.7%		23.7%	
Bootstrap p-value	0.010		0.013		0.038		0.021	
Observations	342	342	342	342	342	342	342	342

Coefficients are from ordered probit regressions; bootstrap standard errors in parentheses; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 5.12: Profile choice: ordered probit regression (treating NH/NT and ES/CS-combi as separate choices)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Female	0.433***	0.366***	0.494***	0.441***	0.289**	0.239*	0.380***	0.330**
	(0.115)	(0.119)	(0.118)	(0.124)	(0.117)	(0.125)	(0.121)	(0.129)
Competitive		-0.142**		-0.133**		-0.113**		-0.129**
		(0.057)		(0.057)		(0.057)		(0.059)
Math grade			-0.036	-0.010			0.124	0.148
			(0.127)	(0.131)			(0.134)	(0.138)
GPA			-0.319***	-0.351***			-0.284***	-0.315***
			(0.103)	(0.104)			(0.106)	(0.108)
Rel Math grade			0.869*	0.873*			0.692	0.698
			(0.462)	(0.476)			(0.466)	(0.481)
Math quartile					0.379***	0.380***	0.360***	0.362***
					(0.080)	(0.082)	(0.078)	(0.081)
Math difficulty					0.096***	0.093***	0.068**	0.066**
					(0.026)	(0.027)	(0.031)	(0.031)
Cut 1	-0.568	-0.610	-2.759	-2.836	0.365	0.326	-0.643	-0.726
Cut 2	-0.006	-0.045	-2.149	-2.224	1.014	0.976	0.015	-0.066
Cut 3	0.372	0.336	-1.723	-1.796	1.463	1.427	0.477	0.398
Cut 4	1.299	1.275	-0.711	-0.773	2.530	2.502	1.576	1.510
Cut 5	1.571	1.552	-0.429	-0.484	2.820	2.797	1.874	1.813
f/(c5-c1)	0.202	0.169	0.212	0.188	0.118	0.097	0.151	0.130
Dif.	16.3%		11.3%		17.8%		13.9%	
Bootstrap P-value	0.006		0.010		0.025		0.014	
Observations	342	342	342	342	342	342	342	342

Coefficients are from ordered probit regressions; bootstrap standard errors in parentheses; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 5.13: Profile choice: ordered probit regression (using students' own ranking)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Female	0.414***	0.350***	0.538***	0.485***	0.324***	0.273**	0.460***	0.406***
	(0.117)	(0.124)	(0.124)	(0.131)	(0.119)	(0.126)	(0.126)	(0.134)
Competitive		-0.127**		-0.121*		-0.104*		-0.122*
		(0.059)		(0.063)		(0.060)		(0.064)
Math grade			0.145	0.167			0.277**	0.298**
			(0.124)	(0.125)			(0.130)	(0.133)
GPA			-0.367***	-0.395***			-0.337***	-0.365***
			(0.109)	(0.110)			(0.110)	(0.113)
Rel Math grade			1.225***	1.216**			1.136**	1.127**
			(0.466)	(0.473)			(0.473)	(0.484)
Math quartile					0.174**	0.178**	0.150*	0.156**
					(0.077)	(0.079)	(0.077)	(0.079)
Math difficulty					0.094***	0.091***	0.070**	0.068**
					(0.027)	(0.028)	(0.032)	(0.032)
Cut 1	-0.251	-0.289	-1.330	-1.413	0.395	0.360	0.246	0.165
Cut 2	0.578	0.546	-0.433	-0.510	1.291	1.261	1.171	1.096
Cut 3	1.505	1.480	0.562	0.491	2.279	2.253	2.193	2.125
f/(c3-c1)	0.236	0.198	0.284	0.255	0.172	0.144	0.236	0.207
Dif.	16.1%		10.2%		16.3%		12.3%	
Bootstrap p-value	0.017		0.026		0.043		0.027	
Observations	354	354	354	354	354	354	354	354

Coefficients are from ordered probit regressions; bootstrap standard errors in parentheses; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.