Gender, Competitiveness and Career Choices*

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Abstract

Gender differences in competitiveness are often discussed as a potential explanation for gender differences in education and labor market outcomes. We correlate an incentivized measure of competitiveness with an 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. The prestigiousness of those profiles perfectly correlates with their math and science intensity. While boys and girls have very similar levels of academic ability, boys are substantially more likely than girls to choose more prestigious profiles. The first main result is that competitiveness is as important a predictor of profile choice as gender. Second, the gender difference in profile choice is significantly reduced when controlling for the gender difference in competitiveness; by up to 20 percent of which four percentage points can be attributed to gender differences in risk aversion and confidence.

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

Gender differences in education and labor market outcomes, though greatly reduced, have remained ubiquitous. To understand gender differences in these outcomes, psychological attributes are commonly discussed as potential explanations.[1] The goal of this paper is to provide evidence of a link

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[1]Bertrand (2011), however, concludes her summary of the laboratory research on gender differences with: "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. More direct demonstrations of field relevance will be crucial for these new perspectives to have a lasting impact on how labor economists approach their study of gender gaps" (p.1583).

between education and competitiveness, which is an attribute for which large gender differences in the laboratory have been widely documented (see Croson and Gneezy, 2009 and Niederle and Vesterlund, 2011). Through in-class experiments we collected data on the competitiveness of high school students which we merged with information about their subsequent education choices. With this data we demonstrate that competitiveness significantly correlates with educational choices and explains an economically and statistically significant part of the gender gap in those choices.

Gender differences in educational choices, particularly regarding intensity in math and science subjects, 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 many other OECD countries.[2] Even in the U.S., however, girls are underrepresented among extremely high achieving math high school students (Ellison and Swanson, 2010), and women are significantly less likely than men to graduate from college with a major in science, technology, engineering or mathematics.[3] 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, 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).[4]

Standard explanations for the gender difference in math are, next to differences in preferences, differences in ability. However, Ellison and Swanson (2010) provide compelling evidence that the gender imbalance in the U.S. among high achieving math students is not driven solely by differences in mathematical ability. Furthermore, 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).

Another potential source for the observed gender differences in math and science are gender differences in psychological attributes as documented by experiments. One large and robust gender difference in experiments is that women are found to be less competitive than men (see Gneezy et al., 2003, Niederle and Vesterlund, 2007 and, for an overview on gender differences, Croson and Gneezy, 2009). It seems plausible that competitiveness is important for educational choices and resulting labor market outcomes. People who shy away from competitive environments may self-select into

[2] We will show that in the Netherlands boys are significantly more likely to take math classes in high school than girls. In France, where like in the Netherlands high school children decide on which sets of classes to enroll in, girls are less likely to choose the math and science heavy options (http://www.insee.fr/fr/themes/tableau.asp?ref_id=eduop709&reg_id=19). The same is true for Denmark (Schroter Joensen and Skyt Nielsen, 2011), Switzerland (http://www.ibe.uzh.ch/publikationen/SGH2003_d.pdf) and Germany (Roeder and Gruehn, 1997).

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

[4] 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.

different, potentially lower paid, careers (Kleinjans, 2009). Competitiveness could be an especially important trait for certain fields such as sciences and mathematics which are male dominated and viewed as competitive.[5] Indeed, there is evidence of low tolerance for competition among women who drop out of math intensive college majors and engineering.[6] However, most of this evidence is fairly casual and may suffer from the problem of reverse causality. Women who drop out of science and engineering may search for explanations such as the negative aspect of the competitive environment.

To assess the existence and potential size of an effect of competitiveness on educational choices, we aim to measure competitiveness before students have different and potentially influential experiences resulting from their choices. We run our study in the Netherlands where, at the end of the third year of secondary school, students in the pre-university track choose between four study profiles which strongly correlate with their choices of major in tertiary education. The four profiles are clearly ranked in terms of their math intensity and academic prestige as follows: science, health, social sciences and humanities. Girls, despite being slightly better academically than boys, are less likely to enroll in the most prestigious math-heavy science profile and more likely to enroll in the least prestigious humanities profile.

We administered an experiment in four schools in and around Amsterdam just before students chose their study profiles. Since we are concerned with the choice of prestigious science profiles typically favored by males, we measure the competitiveness of students in a stereotypical male task. Specifically, we use the most common measure of competitiveness by Niederle and Vesterlund (2007), which has proven to be robust across many settings and subject pools (Niederle and Vesterlund, 2011). Niederle and Vesterlund (2007) show that gender differences in competitiveness can be partially attributed to gender differences in confidence, while gender differences in risk attitudes play only a minor role. Both confidence and risk attitudes could also play an important role when students decide whether to choose a more prestigious study profile. We therefore also administer incentivized measures of students' confidence and their risk attitudes. The schools provided us with the subsequent profile choices of students as well as with their grades. Finally, we assess the students' perceptions of their mathematical ability, as grades may not be the most accurate predictor of ability.

Students in our sample exhibit the expected significant gender gap in prestigiousness (or math intensity) of their chosen study profiles, controlling for both objective and subjective academic performance. Confirming the results from the literature on college students, boys in our sample

[5]Indeed, laboratory research has shown that the large gender differences in competitiveness are sometimes (e.g. Kamas and Preston, 2010) but not always (e,g, Wozniak et al., 2010; see Niederle and Vesterlund, 2011 for an overview) attenuated when assessed in verbal tasks. Furthermore, if more boys select math heavy courses and majors, this increases the number of potential male competitors. Experiments have shown that for women both the performance in (Gneezy et al., 2003) as well as the selection into competitive environments (Niederle et al., 2013; Balafoutas and Sutter, 2012) is reduced when the competition group includes males. Similarly, Huguet and Regner (2007) show that girls underperform in mixed-sex groups (but not in all female groups) in a test they were led to believe measures mathematical ability.

[6]The report "Women's Experiences in College Engineering" (Goodman Research Group, 2002) reports that women do not drop their math intensive studies because of ability, but rather because of low self-confidence. These women also mention negative aspects of their climate such as competition and discouraging faculty and peers (see also Felder et al., 1995, for a study on engineering).

are more than twice as likely than girls to enter the tournament. The first main finding is that competitiveness correlates positively with the prestige of chosen study profiles. Being competitive bridges around 20 percent of the distance between choosing the lowest and the highest ranked profile, which is comparable to the effect of being male. In almost all specifications is the binary measure of competitiveness more predictive of profile choice than the gender dummy. Our main result is that competitiveness accounts for 20 percent of the gender gap in the prestige of chosen study profiles when we control for grades and perceived mathematical ability. When we subsequently also control for confidence and risk attitudes, inclusion of competitiveness closes the gender gap in the prestige of chosen profiles by a significant 16 percent.

Our paper shows the *external relevance* of the concept of competitiveness.[7] The competitiveness measure commonly used in laboratory experiments helps uncover a trait which accounts for a statistically and economically significant portion of the gender difference in educational choices. As such our paper not only shows the external relevance of competitiveness but also validates the specific measure of competitiveness provided by Niederle and Vesterlund (2007).

2 Study Design

2.1 Data Collection

The students participating in this study are drawn from the population of Dutch secondary school students who are enrolled in the pre-university track. Halfway through the six years of secondary school, at the end of 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). We describe the Dutch school system in more detail in Section 3.

We invited secondary schools in and around Amsterdam to participate in a research project investigating the determinants of study profile choices. We demanded one class hour (45 or 50 minutes) of all grade 9 school groups in the pre-university track.[8] The invitation letter stated that students would participate in an in-class experiment and be paid depending on their choices. It also mentioned that after the experiment a short questionnaire would be administered. For detailed instructions see the online appendix.

Four schools cooperated, one in the city of Amsterdam and three in cities close to Amsterdam.[9]

[7] There has been a growing literature on the external validity of lab results on gender differences, most notably competitiveness. We discuss this literature further in the conclusions.

[8] In the first three years of the pre-university track, students are taught in the same school group (or class) of around 25 students for all subjects during the entire school year. Different subjects are typically taught by different teachers.

[9] While a sample of four schools can hardly be representative for the total of over 500 schools that offer the pre-university track, the four schools appear to be average on several dimensions. First, as we will discuss in more detail later, the share of girls and profile choices by gender in the four schools are close to the national averages. Second, the numbers of students in the four schools are (around) 700, 800, 1500 and 2000. The average secondary school size in the Netherlands is close to 1500 (CBS, 2012, p.80). Third, the average grades on the nationwide exams in the final

In each school, we captured all students in grade 9 of the pre-university track for a total of 397 students in 16 groups. Because the schools are geographically dispersed, we do not worry that students received information about the experiment from students in other schools. For any given school, experiments in different school groups were administered on the same day, often at the same time. The data collection in the schools took place in March, April and May of 2011.

After the end of the school year, the schools provided us with the students' final grades and the definite profile choices. For 35 students we do not have such a definite profile choice.[10] For 20 of these students, we can use information about their expected profile choice obtained through the short questionnaire.[11] We drop the remaining 15 students for whom we have neither a definite 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.

2.2 Variables

Competitiveness. 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 then 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 questions (if any), 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 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.[12]

Participants were informed that 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 school group. Participants received details on each round only immediately before performing in the task. Participants did not receive any information about their own performance or the performance of

year in the four schools are 6.2, 6.2, 6.3 and 6.8, where the national average for the pre-university track equals 6.2. Finally, the pass rates on the final exam in the four schools are 0.87, 0.87, 0.91 and 0.95, where the national average for the pre-university track equals 0.88.

[10] Some students may have to retake the year, and in two schools those are included in the final profile choice, in the others not. We cannot observe whether a student retook the grade or advanced to the chosen study profile.

[11] For the students for whom we have both the definite profile choice and the intention stated in the questionnaire, the questionnaire answer accurately predicts the final choice in 93 percent of the cases.

[12] We control for test version fixed effects in all our regressions.

others. They 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 (this includes the payment from incentivized questions to elicit confidence and risk attitudes; see below). There was no participation fee.

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 by computer among students from the same school group 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.

In the third round, participants chose which of the two payment schemes they would prefer. Students were informed that 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 experimental group members in the previous Round 2 tournament. Therefore, just like in Niederle and Vesterlund (2007), the choice was an individual decision as a subject could not affect the payoffs of any other participant.[13]

Confidence. Because the decision to enter the tournament depends on the subjects' beliefs about their relative performance, we elicited those beliefs in the experiment after they completed the Round 3 performance. Specifically, we asked students about their relative performance in the Round 2 tournament compared to the other three experimental group members which are randomly drawn from their school group, from 1 (best) to 4 (worst) of their group of four. If their guess was correct, they received €1.[14]

Risk attitudes. Because the decision to enter the tournament can depend on the risk attitudes of subjects, we elicited risk attitudes by using two measures from the experimental literature. First, following Eckel and Grossman (2002), subjects picked one option among a sure payoff of €2 and four 50/50 lotteries in Euros with 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"). Dohmen et al. (2011), using representative survey data from Germany, find that this simple non-incentivized risk question predicts both incentivized choices in

[13] There are several advantages to having participants compete in Round 3 against the previous Round 2 tournament performance. First, the performance of a subject who chose the tournament is evaluated against the performance of other subjects in a tournament. Second, the choice of compensation scheme of a subject should 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.

[14] 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.

a lottery task as well as 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.

Objective ability. We use information about students' grades at the end of 9th grade provided by the schools to construct three objective ability measures. The first is GPA, the second is the grade for mathematics. In the Dutch school system, grades are expressed on a scale from 1(worst) to 10(best), where 6 is the first passing grade. The third measure is the relative math grade in the student's group. We gave the best students in their group a rank of 1. The rank of each student is equal to 1 plus the number of students with a strictly better grade. We then normalize the measure by dividing by the number of students in the group.[15]

Subjective ability. Since grades need not be a good predictor of mathematical ability, we collected subjective ability measures in the questionnaire that was administered after the in-class experiment. 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%).[16] 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). While both those questions may yield a better assessment of mathematical ability, they could in addition be a measure of confidence, which in turn could influence study profile choices. Indeed, it has been found that conditional on academic performance, boys are more confident in their relative ability than girls (Eccles, 1998), a difference that seems greatest among gifted children (Preckel et al., 2008).

We present the results from the study in three stages. First, we describe the environment and study profile decisions of students. We document significant gender differences in the prestige (and math intensity) of the profile choices which are not explained by differences in ability. Second, we present the data on the experimentally measured attributes: competitiveness, confidence and risk aversion. We show significant gender differences in competitiveness, that is selection into the tournament conditional on performance. We assess the extent to which these differences can be attributed to gender differences in confidence and risk attitudes. Finally, in the main result section we examine whether competitiveness correlates with profile choice. We then assess to what extent gender differences in competitiveness can account for gender differences in the prestige of chosen profiles.

[15] To compute the relative mathematics rank in the group, we include all students in our sample for whom we have grades, including the students we had to drop for the final results.

[16] 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 three 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. Clearly "wrong" answers consist of the yes/yes/no and yes/no/yes patterns. All other patterns can be rationalized by (i) students truly understanding the question or (ii) misreading the question and answering yes only to their own quartile. There are 10 answers that follow the yes/yes/no pattern and zero that follow the yes/no/yes pattern.

3 The Education Choice

3.1 Study Profiles

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 first takes place when students go from primary school - grades 1 to 6 - to secondary school, normally at age 12. There are three tracks: around 20 percent of students graduate from the six-year pre-university track, 25 percent from the five-year general track and 55 percent from the four-year 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. Girls are somewhat more likely to go to the pre-university track, making up 53 percent of the students (Statistics Netherlands).

Halfway through the six years of secondary school, at the end of grade 9, students in the pre-university track have to choose one 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)
- the humanities-oriented profile Culture & Society (CS)

Each student can select any profile, though low grades in specific subjects may lead to teachers recommending other profiles.

For each study profile, Table 1 shows the subjects offered and the number of teaching hours assigned to these subjects in the last three years of secondary school. Mathematics is the only subject taught at different levels in each track, where D is the most advanced math course followed by B, A and C. The order of math and science difficulty is therefore NT>NH>ES>CS. There is also a strong correlation between the study profile in secondary school and the choice of major in tertiary education. 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 (Statistics Netherlands, 2006).[17]

Generally, NT is viewed as the most challenging and prestigious study profile, followed by NH and ES. CS is seen as the least demanding and least prestigious study profile. This order is related to the difficulty and amount of mathematics and science in the curriculum. In other countries in

[17] The tertiary education distribution by study profile is as follows: Of students in the NT track, 64% study Science and Engineering, 15% Economics and Business and 9% a subject in the Humanities and 7% Health Care. For NH students, 48% study in Health care, 18% in Science and Engineering, 9% in Social Sciences and 8% in Economics and Business. For ES students, 46% study in Economics and Business, 20% in Law, 19% in Social Sciences and 8 % in Humanities. For CS students 34% study in Social Sciences, 30% in Humanities and 20% in Law. For details see Table A.3 in the online appendix. The data are from Statistics Netherlands, 2006. Some studies actually restrict entry to certain profiles or courses within profiles. For example, medical schools require NT or NH; to study Math, having taken at least Math B in high school is required.

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. In addition all 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. Source: Ministry of Education, Culture and Science.

which students can choose study profiles in school, the prestigiousness of the profiles is also often highly correlated with their math intensity (see for example Pautler, 1981, for France).

The prestigiousness of study profiles is related to the likelihood of going to university: Students in the NT track have an 81% chance to go to university, followed by NH students (72%) and ES students (69%), while only 60% of CS students go to university (Statistics Netherlands, 2006).

This ordering of study profiles is related to the academic performance of the students from our sample that select various profiles. The top panel of Table 2 shows mean values of measures of students' objective and subjective ability by study profile. According to all five of our ability measures, the students who choose NT have higher ability than the students who choose NH, who in turn have higher ability measures than the students who choose ES. Students who choose CS score lowest on four of the five measures.

This ordering of profiles by prestige is also reflected in the opinions of the students from our study. In the short questionnaire we asked the students to rank the four study profiles by asking "Which profile do the best students pick?". The bottom panel of Table 2 shows that their responses concur with the general opinion. A majority of over 70 percent of students believes NT is chosen by the best students. A majority of students ranks the NH study profile second and ES third. More than 80 percent of students rank CS as the profile most chosen by the weakest students. The rankings of boys and girls are very similar. We also asked students to rank the four study profiles

Table 2. Student ability and perceived prestigiousness of study profiles given their profile choice

By chosen profile	NT	NH	ES	CS	Difference
GPA (1-10)	7.12	7.09	6.65	6.61	0.00
Math grades (1-10)	7.25	6.73	6.20	6.21	0.00
Relative math (0-1)	0.23	0.35	0.46	0.49	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
All: Prestige (% rank)	1.48 (71%)	2.13 (57%)	2.64 (60%)	3.67 (81%)	
Boys: Prestige (% rank)	1.43 (75%)	2.24 (57%)	2.59 (56%)	3.68 (82%)	
Girls: Prestige (% rank)	1.52 (68%)	2.03 (57%)	2.71 (64%)	3.66 (80%)	
Observations	102	89	128	43	

Note: Top rows: Average characteristics of subjects who chose that profile among the 362 students in our sample. 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. Bottom rows: Average perceived ranking of prestigiousness 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.

in terms of future earnings. The picture that emerges is very similar.[18]

In the remainder of the paper, we order the profiles from most to least prestigious: NT>NH>ES>CS. As a robustness check, we use in the online appendix for each student the ranking they gave to their chosen profile in terms of which profiles the best students choose. That is, if a student ranked, say, CS as the profile chosen by the best students, followed by ES, NH and NT (so, the reverse order) and chose profile CS for herself, we categorize that student as choosing the most "own prestigious" profile (rank 4). If this student chose ES, we would rank her choice as 3 and so on. The main results of this paper remain qualitatively the same.

Profile choices differ markedly between the sexes in the Netherlands. Boys are more likely to choose more prestigious study profiles. Compared to girls, boys are almost twice as likely to choose the most prestigious profile, NT, 43 percent compared to 23 percent. The NH profile is chosen slightly less often by boys than girls (17 compared to 26 percent). The ES profile is chosen by 35 percent of boys and 32 percent of girls. Boys are only a third as likely to choose the least prestigious profile, CS, (5 percent compared to 18 percent).[19] The fact that girls are disproportionally 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 remain as they are for now.[20]

[18]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. 50 percent think that NT gives the best salary prospects, 27 percent think NH, 20 percent ES and 2 percent CS.

[19]Source: Statistics Netherlands (CBS) 2012. Some schools allow students to choose combination profiles, NT/NH and ES/CS. In the numbers above, we categorize NT/NH-combi students as NT students and ES/CS-combi students as ES students. In Table A.2 of the appendix, we compare the choices of students in the Netherlands to the ones in our sample using different ways to allocate combination students.

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

3.2 Academic Data

Before we assess the profile choices of boys and girls in our data, we present summary statistics of academic ability and study profile choices by gender.

Ability. The first three rows of Panel A in Table 3 show that girls have a significantly higher GPA than boys, while there is no significant gender difference in the absolute or relative grade for mathematics. The last two rows of Panel A in Table 3 show that there are, however, significant gender differences on the two subjective measures of mathematical ability (math quartile and math difficulty), with girls feeling less able than boys.

Profile choice. We have two sources of information about students' profile choices. In the questionnaire we asked students which profile they expected to choose. The schools provided us with information about their actual choices made several months later. Two of the four schools in our sample allow students to pick combined profiles. Of the 173 students in those two schools, 64 students choose the NT/NH combination and 18 the ES/CS combination. In the NT/NH profile, students take Mathematics B but 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 somewhat in between the pure profiles, though a little closer to NT and ES, respectively. For the main analysis of this paper we use for the students in combined profiles the chosen profile as stated in the questionnaire.[21] 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 in the online appendix. As a further robustness check, in the online appendix, we show results where we treat NT/NH and ES/CS as separate categories.[22] The results remain qualitatively the same in both specifications.

3.3 Gender Differences in Prestige of Chosen Profiles

While academically boys and girls are very comparable, girls make significantly different profile choices from boys. The lower part of Table 3 shows profile choices by gender in our sample of 362 students. The pattern is similar to the pattern observed in the 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 much 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 science profiles (NT or NH) compared to one of the society profiles (ES or CS). The girls in our sample are therefore quite similar to the national statistics where 49 percent of girls pick a science

[21] All of the students who picked ES/CS chose ES or CS in the questionnaire. All of the students who picked NT/NH chose NT or NH in the questionnaire with the exception of one student who chose CS. We treat this student as a CS student when using the stated profile to place students that chose a combination profile into "pure" profiles. See Table A.2 in the appendix for the number of students who pick NT/NH or ES/CS.

[22] For these two analyses we drop an additional 20 students. These are all the students for whom we have not received a final profile choice from the schools and used the questionnaire answer instead. The questionnaire, however, did not allow for combination profiles.

Table 3. Ability and profile choices by gender

	Boys	Girls	p-value
A: Ability			
GPA (1-10)	6.80	6.97	0.01
Math grade (1-10)	6.67	6.59	0.49
Math relative (0-1)	0.38	0.37	0.88
Math difficulty (0-10)	3.41	4.18	0.01
Math quartile (1(best)-4)	1.97	2.25	0.03
B: Profile choices			
Nature & Technology (NT)	0.40	0.17	
Nature & Health (NH)	0.12	0.36	
Economics & Society (ES)	0.39	0.32	
Culture & Society (CS)	0.08	0.15	0.00
Number of observations	177	185	

Note: Panel A: Average characteristics by gender among the 362 students in our sample. 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%. Panel B: Shares of boys and girls choosing each of the four study profiles among the 362 students in our sample. The last column reports p-values from t-tests for continuous variables and from a Fisher's exact test for categorical variables.

profile. However, the national statistics show boys to be slightly more likely to pick a science profile than our sample (60 percent vs. 52 percent).[23]

To more precisely understand gender differences in the prestige of the chosen study profiles, we show in Table 4 ordered probit regressions where we order profiles from most to least prestigious: NT>NH>ES>CS. In this and all following analyses, we standardize all non-binary control variables to have mean zero and a standard deviation of 1, in order to make the coefficients comparable. Table A.1 in the online appendix provides the mean and standard deviations of all our control variables. The first column shows that boys are significantly more likely than girls to choose a prestigious profile. Being female bridges over 18 percent of the distance between the most and the least prestigious profiles (this is shown in the penultimate row by Female/(C3-C1), the female coefficient divided by the distance between the first and the third ordered probit cutoffs). Inclusion of objective ability variables (column (2)) increases the gender gap to 22 percent of the distance between the most and the least prestigious profiles. Note that the coefficient on female is larger (in absolute value) than on the GPA. An increase of one standard deviation in GPA corresponds to bridging 13 percent of the gap between the most and the least prestigious profile.

When we add students' perceptions about their mathematics ability in column (3), the gender gap shrinks but remains large and highly significant. While these subjective 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.[24]

[23]With 51 percent, the proportion of girls in our sample is close to the national average of 53 percent in pre-university schools.

[24]Alternatively, when we use simple OLS regressions, where CS is modeled as a choice of 1 up to NT as a choice

Table 4. Determinants of profile choice; no psychological attributes

	Ordered probit (NT>NH>ES>CS)			NT vs. Rest	Rest vs. CS
	(1)	(2)	(3)	(4)	(5)
Female	-0.325***	-0.443***	-0.319**	-0.204***	-0.059*
	(0.115)	(0.124)	(0.126)	(0.046)	(0.032)
Math Grade		0.174	-0.074	-0.032	-0.027
		(0.187)	(0.192)	(0.088)	(0.037)
GPA		0.250**	0.244**	0.043	0.031*
		(0.098)	(0.097)	(0.043)	(0.019)
Rel. Math Gr.		-0.155	-0.145	-0.115	-0.016
		(0.152)	(0.152)	(0.079)	(0.030)
Math Difficulty			-0.240***	-0.110**	-0.024
			(0.089)	(0.045)	(0.016)
Math Quartile			-0.315***	-0.155***	-0.029*
			(0.074)	(0.038)	(0.015)
Cut 1 (C1)	-1.423***	2.120	-0.625		
Cut 2 (C2)	-0.307**	3.358**	0.714		
Cut 3 (C3)	0.353**	4.113***	1.538		
Female/(C3-C1)	-0.183***	-0.222***	-0.148***		
N	362	362	362	362	362

Note: Dependent variable in columns (1) to (3): Profile choice, where NT>NH>ES>CS. Coefficients from ordered probit regressions. Dependent variable in column (4): dummy variable NT=1. Dependent variable in column (5): dummy variable "not CS"=1. Marginal effects in columns (4) and (5) from probit regressions. All regressions control for school fixed effects. Robust standard errors in parentheses; *, ** and *** denote significance at 10, 5 and 1 percent, respectively; p-values for Female/(C3-C1) are bootstrapped. The margins are taken for a male student and mean values of the other variables.

Table A.4 in the online appendix shows that the results are very similar when we classify an NT/NH combined choice as NT, and an ES/CS choice as ES, instead of using the students' answer in the questionnaire to attribute combined profile choices to one of the four baseline study profiles. The results are also robust to treating the combined profiles as their own category, where combined profiles are ordered between the baseline study profiles, that is, NT>NT/NH>NH>ES>ES/CS>CS. Finally, using the student-specific ordering and running the same ordered probit specifications, we find that the gender differences are, if anything, slightly exacerbated (see the last three columns of Table A.4 in the online appendix).

To provide additional insights on the magnitude of the gender difference in profile choice, we run probit regressions on choosing the most prestigious profile, NT, compared to any other profile, controlling for objective and subjective academic performance. Column (4) in Table 4 shows that girls are 20 percentage points less likely to choose NT, a significant difference. When we redo the exercise for choosing any profile but the least prestigious profile, CS, the marginal coefficient shows that female students are 6 percentage points more likely to choose CS than boys, again a significant difference (column (5)).

4 Gender Differences in Competitiveness

In this section we analyze gender differences in competitiveness as well as confidence and risk aversion.

4.1 Experimental Data

Competitiveness. Panels A and B of Table 5 report mean values of performance in Rounds 1 and 2 and of tournament entry, separately for boys and girls. In the Round 1 piece rate boys perform significantly better than girls. In the second round when students' payment is based on the tournament, there is no significant difference in performance. Since students compete only against students in their own group, we compute for each student the chance to win the tournament in Round 2 given their performance and that of their school groupmates.[25] The average chance to win the tournament is slightly but not significantly higher for boys than for girls. 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 expected earnings when choosing to enter the tournament in Round 3. This would result in 38 percent of the boys and 35 percent of the girls entering the tournament, an insignificant difference. Actual tournament entry shows a very

of 4, the coefficient on female is -0.277 (s.e. 0.106, $p<0.01$) controlling only for school fixed effects. The magnitude of the effect increases to -0.341 (s.e. 0.099, $p< 0.01$) when we add the controls from column (2) in Table 4, which is slightly larger than the coefficient on standardized GPA which is 0.209 (s.e. 0.071, $p<0.01$). When we add all the controls from column (3) the gender coefficient is -0.215 (s.e. 0.094, $p<0.05$), again larger than the coefficient on the GPA of 0.193 (s.e. 0.066, $p< 0.01$).

[25] To compute the chance of winning the tournament for each participant, we include all 397 students in our sample, including the 35 students we had to drop for the final results. We use simulations and randomly draw one thousand different comparison groups of three from a participant's own school group. 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. Descriptive statistics of performance on task and psychological attributes by gender

	Scale	Boys	Girls	p-value
A: Performance				
Performance Round 1 (piece rate)	number of correct answers	6.60	5.94	0.03
Performance Round 2 (tournament)	number of correct answers	7.90	7.42	0.15
Chance of winning Round 2 (tournament)	[0,1]	0.27	0.24	0.24
B: Competitiveness				
Actual tournament entry	dummy	0.49	0.23	0.00
Optimal tournament entry	dummy	0.38	0.35	0.59
C: Confidence				
Actual guessed rank	1(best) - 4 (worst)	2.14	2.56	0.00
Optimal guessed rank	1(best) - 4 (worst)	2.39	2.55	0.24
Guesses to be the best	dummy	0.32	0.11	0.00
Optimal to guess to be the best	dummy	0.25	0.22	0.46
Actual guessed rank is correct	dummy	0.38	0.34	0.44
D: Risk Attitudes				
Lottery choice	1(no risk) - 5(highest risk)	3.46	2.99	0.00
Risk taking	0(avoid risk) - 10(seek risk)	6.52	5.96	0.00
Number of observations		177	185	

Note: The table reports average values of variables by gender based on 362 students. Panel A: Performance is number of correct answers on addition tasks under piece-rate and tournament incentives. Chance of winning Round 2 is based on simulations drawing 1000 different comparison groups of three from a participant's own school group. Panel B: Actual tournament entry is share choosing the tournament scheme in Round 3. Optimal tournament entry is the share that has higher expected payoff under tournament than under piece-rate in Round 3. Panel C: Actual guessed rank is guessed rank in tournament in Round 2. Optimal guessed rank is the guessed rank in Round 2 that maximizes expected payoffs. Optimal to guess to be the best is the share for whom the guessed rank in Round 2 to be the best maximizes expected payoffs. Actual guessed rank is correct is one if guessed rank is the correct rank in comparison with three randomly drawn students from one's own school group. Panel D: Lottery choice is choice between five lotteries increasing in riskiness and expected payoffs. Risk taking is response to the question whether someone sees her/himself as someone who is fully prepared to take risks (10-highest) or someone who tries to avoid taking risks (0-lowest). The last column reports p-values from t-tests for continuous variables and from a Fisher's exact test for categorical variables.

different pattern; we find that 49 percent of boys and less than half as many, 23 percent of girls, enter the tournament. This difference is significant (and significantly different from optimal entry p=0.01).[26]

Confidence. Panel C of Table 5 reports that the average guessed rank is 2.14 for boys and 2.56 for girls, with the two distributions being significantly different. We find that 32 percent of the boys and 11 percent of the girls believe that they are the best performers within their group, again a significant difference. To assess the accuracy of these beliefs, we compute for each student the optimal guessed rank, that is, the guess that would have maximized their expected earnings, given

[26]In Round 3, subjects who compete solve on average 9.75 correct sums while those who do not compete solve 7.92 (p=0.00). The overall average is 8.57. Neither for the subjects who enter the tournament nor for those who choose the piece-rate is performance significantly different between the genders (p=0.25 and p=0.65, respectively).

the performances of the other students in their school group.[27] Using the optimal guessed rank, there would be no significant gender difference in overall beliefs or the guess to be the best. An ordered probit regression of the guessed rank on the optimal guessed rank and a female dummy delivers a female coefficient of 0.496 (s.e. 0.117, p = 0.00).[28] This confirms that girls, given their relative performance, are significantly less confident about their relative performance than boys.

Panel C also shows that 38 percent of the boys and 34 percent of the girls guess the rank that maximizes their expected payoffs. These shares are quite similar to the shares of correct guesses in Niederle and Vesterlund (2007), who report that 30 percent of the men and 38 percent of the women guess their rank correctly. This indicates that the beliefs about the ability of potential competitors of the students in the classroom experiment are as accurate (or inaccurate) as those of participants in an anonymous laboratory setting.

Risk attitudes. Panel D in Table 5 shows that boys on average choose a significantly more risky lottery. On the general risk tolerance question boys also score on average significantly higher. The correlation between the two risk measures is 0.42 in the whole sample ($p<0.01$), and 0.45 and 0.34 in the sub-samples of boys and girls, respectively ($p<0.01$ in both cases).

4.2 Gender Differences in Competitiveness

To assess gender differences in competitiveness, Table 6 shows marginal effects from probit regressions of tournament entry in Round 3. Girls have a 26 percentage point lower probability of entering the tournament compared to boys, when only controlling for performance in Round 1, the difference in performance between Rounds 1 and 2, the chance of winning in Round 2, school fixed effects and test version fixed effects (column (1)). This is very much in line with Niederle and Vesterlund (2007) and the large resulting literature (see Niederle and Vesterlund, 2011).

Adding the guessed rank as a measure of confidence to the probit regression on tournament entry, column (2) shows that the gender effect drops to 19 percentage points, a still highly significant difference.[29] Adding the lottery choice variable slightly reduces the gender gap in tournament entry by an additional 3 percentage points to 16 percentage points (compare columns (2) and (3)). Adding the questionnaire-based risk measure reduces the gender gap by another percentage point (compare columns (3) and (4)). Finally, also including measures of academic performance and of perceived

[27] We compute the optimal guessed rank through simulation. We randomly draw a thousand different comparison groups of three from a participants' own school group. We include all 397 students in our sample, including the 35 students we had to drop for the final results. 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 a place, both guesses were counted as correct.

[28] The coefficient on the optimal guessed rank is 0.653 (s.e. 0.060, p=0.00).

[29] Since the task is a mathematics task, we could alternatively 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 5 percent and a gap of 25 percentage points remains. The coefficient on female is -0.249, (s.e. 0.049, $p<0.01$), not very different from the -0.264 from column (1). Adding all measures on beliefs about one's relative performance and math ability does not reduce the coefficient on female compared to just having the belief on tournament performance (guessed rank). Female students are then 18.6 (s.e. 5.4, $p<0.01$) percentage points less likely to enter the tournament.

Table 6. Determinants of tournament entry

	(1)	(2)	(3)	(4)	(5)
Female	-0.264***	-0.188***	-0.155***	-0.144**	-0.145**
	(0.051)	(0.055)	(0.055)	(0.057)	(0.059)
Tournament	0.056***	0.023	0.021	0.021	0.012
	(0.021)	(0.021)	(0.021)	(0.022)	(0.021)
T - PR	-0.036***	-0.030**	-0.028**	-0.027*	-0.024*
	(0.014)	(0.014)	(0.014)	(0.014)	(0.014)
Win Prob	0.245	0.078	0.069	0.053	0.159
	(0.208)	(0.213)	(0.218)	(0.220)	(0.228)
Guessed rank		-0.283***	-0.284***	-0.266***	-0.255***
		(0.041)	(0.041)	(0.042)	(0.043)
Lottery			0.122***	0.066*	0.063*
			(0.033)	(0.034)	(0.035)
Risk-taking				0.158***	0.177***
				(0.036)	(0.036)
Math grade					0.184*
					(0.099)
GPA					-0.080
					(0.051)
Math Relative					0.045
					(0.080)
Math quartile					0.064
					(0.043)
Math difficulty					-0.023
					(0.046)
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). All regressions control for school fixed effects and test version fixed effects. Standard errors of the marginal coefficients are in parentheses; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$ of the underlying coefficient.

mathematical ability, the gender gap in tournament entry stays the same, leaving a significant gender gap in tournament entry of 15 percentage points (column (5)).

In summary, the 15 year old children in our sample follow the standard gender differences in choice of competition observed with college students (see Niederle and Vesterlund, 2011). Controlling for performance, girls are about 26 percentage points less likely to enter the tournament. Boys have significantly more optimistic views about their relative performance than girls, and these gender differences in confidence account for slightly under 30 percent of the gender gap in tournament entry. Risk attitudes, whether measured by a lottery choice or a simple questionnaire item, while significantly predicting tournament entry, reduce the gender gap in competitiveness only by a much smaller amount once we control for confidence.

5 Can Competitiveness Account for Gender Differences in Prestige of Chosen Profiles?

The students in our sample represent a classical situation. Boys and girls agree on which academic profiles are the most prestigious, where prestigiousness perfectly correlates with math intensity. They do not differ in math grades, and if anything, girls have a slightly higher GPA 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 and perceived mathematical ability. The students in our sample also exhibit the standard gender gap in competitiveness.

In this section we assess whether competitiveness correlates with the prestigiousness of the study profile choice and, more importantly, whether gender differences in competitiveness can help account for the gender gap in chosen profiles. We also confirm that our results are robust to the inclusion of different sets of ability control variables, controls for confidence and risk attitudes which we showed to be correlated with tournament entry, and a final set of controls for socioeconomic background.

To assess the effect of competitiveness on the choice of study profile, we run ordered probit regressions on the ranked profile choice. We always include controls for performance in Rounds 1 and 2 of the experiment, the chance of winning the Round 2 tournament, school fixed effects and test version fixed effects (which are not reported in the table). To provide a flavor of the results, in a first regression not presented in Table 7 we only include the female dummy. The coefficient on the female dummy is -0.333 (s.e. 0.118, $p<0.001$). Given the estimates of Cut 1 and Cut 3, being female bridges 18.4 percent ($p<0.001$) of the gap between choosing the most and the least prestigious profile.[30] We then add competitiveness, which takes a value of 1 for a student who entered the tournament in Round 3 of the experiment and 0 if the student chose the piece rate. The first result is that the coefficient on competitiveness is significant, 0.373 (s.e. 0.131, $p < 0.01$), with more competitive students choosing more prestigious profiles. The decision to enter the tournament bridges 20.4 percent of the gap between choosing the least and the most prestigious profiles.[31]

[30] Cut 1 is estimated to be -1.180 ($p<0.001$), Cut 2 is -0.049, and Cut 3 is 0.625 ($p<0.05$).

[31] In this regression, Cut 1 has a value of -1.166 ($p<0.001$), Cut 2 is -0.20, and Cut 3 equals 0.661 ($p<0.05$).

Competitiveness has a larger effect than the gender of the student: the coefficient on female is -0.250 (s.e. 0.122, p<0.05) which bridges 14 percent of the gap. In fact, when there is no other information available, knowing a students' competitiveness is a slightly better predictor of study profile choice than knowing their gender.[32] The second result is that competitiveness significantly reduces the effet of gender on profile choice: While female bridged 18.4 percent of the gap between choosing the least and the most prestigious profile, it is reduced by 25.9 percent (p<0.003) down to 13.7 percent (p<0.05) when we add competitiveness.[33]

We explore this kind of analysis in Table 7. The first result is that the variable competitiveness is significant in an ordered probit regression where we control in addition to female and the basic controls also for objective and subjective academic ability. The coefficient is significant and being competitive bridges 15 percent of the gap between choosing the least and the most prestigious profiles. Competitiveness has a larger effect than the gender of the student: the coefficient on female bridges 12.3 percent of the gap.[34] The main finding is that adding competitiveness in column (2) significantly changes the effect of being female from 0.154 to 0.123, a reduction of 20 percent. This change in the gender effect upon inclusion of our competitiveness measure is significant at the 1-percent level. This shows that gender differences in competitiveness which have been uncovered in laboratory experiments can help account for the gender gap in educational choices, specifically study profile choices, even after controlling for academic performance and perceived mathematical ability.

The online appendix shows that the results remain qualitatively and quantitatively similar when we use other specifications for combined profile choices, or when we use for each student their own specific ordering of prestigiousness of profiles.

We have previously shown that tournament entry is partially explained by confidence and risk attitudes. These attributes could also conceivably be correlated with profile choice. In what follows, we assess the impact of competitiveness on profile choice and its impact on gender differences when accounting for confidence and risk attitudes. For a preliminary analysis, Figure 1 shows for each profile the mean competitiveness of boys and girls who chose that profile. In the figure, competitiveness is measured as the residual from a regression of tournament entry on the measures of performance in the experiment, the guessed rank and the risk measures (plus school and test version fixed effects). For each gender, more competitive students select more prestigious profiles. This indicates that the impact of competitiveness on the profile choice is not due to the impact of risk attitudes and confidence.

In columns (3) to (8) of Table 7 we add controls for confidence and risk attitudes to ordered

[32] When running the ordered probit on tournament entry only (controlling for performance, school fixed effects and test version fixed effects), Entry/(C3-C1) is 0.243 compared to using female only, where Female/(C3-C1) is 0.184. Adding a female dummy to an OLS regression increases the R^2 by 0.019 while adding entry raises it by 0.029 (adding entry on top of female raises the R^2 by a further 0.019 to a total of 0.075).

[33] We use bootstrap to calculate the significance of this difference. This is done by resampling 10,000 times with replacement, keeping the number of male and female subjects constant. We then count the fraction of differences between column (2) and column (1)'s Female/(C3-C1) variable that are negative or zero.

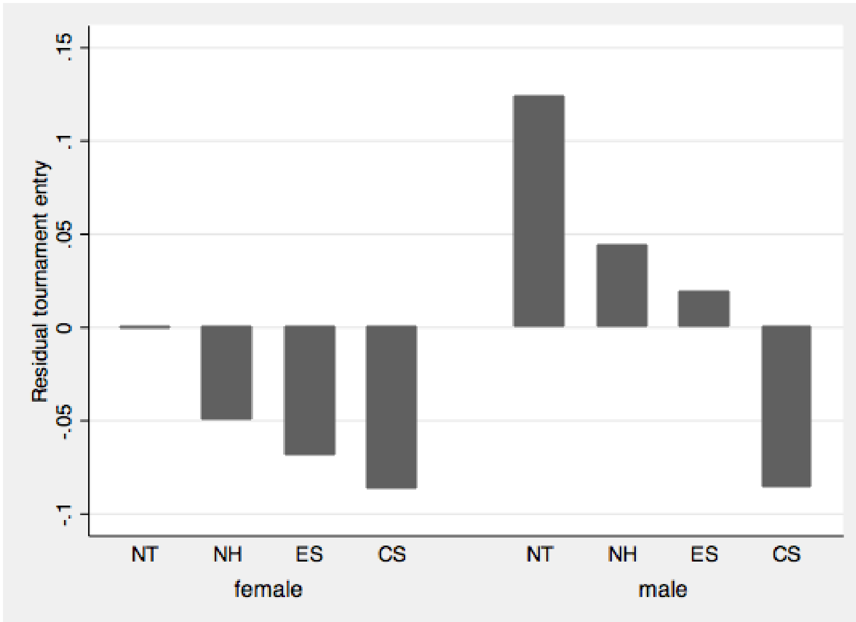
[34] When running the ordered probit on tournament entry and all the basic controls (except the female dummy), Entry/(C3-C1) is 0.180 compared to Female/(C3-C1) in column (1) which is 0.154. Adding a female dummy to an OLS regression with all the controls used in Column (3) increases the R^2 by 0.012 while adding entry raises it by 0.015 (adding entry on top of female raises the R^2 by a further 0.010 to a total of 0.329).

Table 7. Determinants of profile choice, including psychological attributes

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Female	-0.337***	-0.272**	-0.355***	-0.299**	-0.283**	-0.230*	-0.301**	-0.256*	-0.292**	-0.252*
	(0.129)	(0.134)	(0.130)	(0.134)	(0.132)	(0.134)	(0.132)	(0.134)	(0.141)	(0.143)
Entry		0.333**		0.425***		0.336**		0.414***		0.371**
		(0.135)		(0.144)		(0.143)		(0.152)		(0.158)
Math grade	-0.094	-0.150	-0.078	-0.129	-0.113	-0.170	-0.097	-0.148	-0.133	-0.183
	(0.193)	(0.196)	(0.193)	(0.195)	(0.196)	(0.198)	(0.196)	(0.197)	(0.210)	(0.210)
GPA	0.250***	0.279***	0.248***	0.282***	0.252***	0.273***	0.251***	0.277***	0.245**	0.270***
	(0.095)	(0.095)	(0.095)	(0.095)	(0.095)	(0.095)	(0.095)	(0.095)	(0.101)	(0.101)
Math relative	-0.168	-0.187	-0.164	-0.183	-0.174	-0.189	-0.171	-0.185	-0.237	-0.249
	(0.156)	(0.157)	(0.155)	(0.156)	(0.159)	(0.160)	(0.158)	(0.158)	(0.165)	(0.165)
Math difficulty	-0.225**	-0.218**	-0.228**	-0.224**	-0.244***	-0.242***	-0.246***	-0.246***	-0.271***	-0.274***
	(0.089)	(0.089)	(0.090)	(0.090)	(0.093)	(0.092)	(0.094)	(0.094)	(0.102)	(0.101)
Math quartile	-0.329***	-0.336***	-0.334***	-0.350***	-0.338***	-0.345***	-0.343***	-0.357***	-0.338***	-0.352***
	(0.076)	(0.076)	(0.076)	(0.077)	(0.077)	(0.077)	(0.077)	(0.078)	(0.081)	(0.081)
Guessed rank			0.060	0.143*			0.061	0.131	0.031	0.090
			(0.079)	(0.083)			(0.081)	(0.086)	(0.087)	(0.091)
Risk					-0.059	-0.103	-0.049	-0.092	-0.100	-0.139*
					(0.068)	(0.069)	(0.068)	(0.069)	(0.074)	(0.075)
Lottery					0.181**	0.169**	0.181**	0.165**	0.213***	0.200***
					(0.073)	(0.074)	(0.074)	(0.074)	(0.075)	(0.075)
Socio-economic and age cont.									√	√
Cut 1	-0.645	-0.705	-0.375	-0.072	-0.583	-0.891	-0.253	-0.260	-4.050	-3.659
Cut 2	0.712	0.666	0.983	1.303	0.795	0.498	1.124	1.131	-2.585	-2.183
Cut 3	1.547	1.508	1.819	2.151	1.637	1.348	1.967	1.985	-1.676	-1.263
Female/(C3-C1)	-0.154***	-0.123**	-0.162***	-0.134**	-0.128**	-0.103**	-0.136**	-0.114**	-0.145**	-0.126**
Diff.	20.0%		17.1%		19.4%		16.1%		12.9%	
Bootstrap p-value	0.009		0.005		0.014		0.012		0.024	
Observations	362	362	362	362	362	362	362	362	358	358

Note: Coefficients are from ordered probit regressions, where NT>NH>ES>CS. All specifications include controls for performance in Rounds 1 and 2 of the experiment, the chance of winning the Round 2 tournament, school fixed effects and test version fixed effects. The socio-economic controls in columns (11) and (12) consist of 14 name catergory dummies. The age control in columns (11) and (12) is relative age measured in days. Robust standard errors in parentheses; p-values for Female/(C3-C1) and Diff. are bootstrapped; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. The impact of confidence (comparing columns (3) and (5)) and risk attitudes (comparing columns (3) and (7)) on the gender gap (Female/(C3-C1)) and the associated p-values are 5.3% (increasing) (p=0.76) and 16.0% (decreasing) (p=0.02), respectively.

Figure 1. Tournament entry by gender and subsequent profile choice (conditional on performance, confidence and risk attitudes)



Note: The vertical axis measures the residual from a regression of tournament entry on performance on the task, confidence and risk attitudes. The bars indicate the average values of these residuals among students that chose the different profiles by gender.

probit regressions on profile choice ranked by prestigiousness. The main result is that the coefficient of tournament entry and its effect on the gender gap in profile choice remain robust and stay significant throughout. To evaluate the effect of competitiveness, note that the coefficient on entry is between 142 and 162 percent of the coefficient on gender.[35]

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, when controlling for either confidence, risk attitudes, or both. Column (2) shows that competitiveness reduces the gender gap in prestigiousness of profile choice by 20 percent when controlling for actual and perceived academic ability. When we control in addition for both confidence and risk aversion measures, competitiveness still reduces the gender gap by 16 percent (column (7) versus column (8)). Together, all three behavioral measures reduce the gender gap in profile choice by 26 percent (column (1) versus (8)). Using only competitiveness resulted in a reduction of the gender gap that is 78 percent of the size of the effect of all psychological attributes. The result holds when we consider other specifications of combination profiles or use the students' own ranking of prestigiousness of profiles (see online appendix).[36]

[35]When running the ordered probit on tournament entry and all the controls (except the female dummy) in column (7) of Table 7, Entry/(C3-C1) is 0.203 compared to Female/(C3-C1) in column (7) which is -0.136. Adding a female dummy to an OLS regression with all the controls used in Column (7) increases the R^2 by 0.009 while adding entry raises it by 0.016 (adding entry on top of female raises the R^2 by a further 0.013).

[36]When we classify combination profiles as the more prestigious profile in the combination, competitiveness alone

We can also consider the effect of confidence and risk measures on profile choice and its gender gap separately. Column (3) shows that confidence (as measured by the guessed rank in the Round 2 tournament, while we keep controls for the performance in Rounds 1 and 2) has no significant influence on the prestige of the chosen profile. Comparing columns (1) and (3) reveals that the inclusion of the confidence measure also has no impact on the gender gap in choices (which in fact increases slightly). These conclusions are mirrored when we control in addition for competitiveness (see columns (2) and (4)). The results are robust to other specifications of profiles.

Column (5) of Table 7 shows that risk attitudes correlate with the prestige of the chosen profile. Students who opted for a more risky lottery enroll in more prestigious study profiles. Comparing columns (1) and (5) shows that adding risk attitudes reduces the gender gap by around 16 percent (this reduction is significant at the 5 percent level). The effects of competitiveness and risk attitudes on the gender gap in profile choice are almost orthogonal; adding only competitiveness reduces the gender gap by 20 percent (compare columns (1) and (2)); adding only risk attitudes reduces the gender gap by 16 percent (compare columns (1) and (5)); adding competitiveness and risk attitudes together reduces the gender gap by 33.1 percent (compare columns (1) and (6)). The effect of risk attitudes on the gender gap in study profile choices is somewhat variable (and not always significant) in our alternative specifications where it ranges from 6 to 18 percent (see online appendix).[37]

Finally, in the online appendix we include tables for various robustness checks. In all of the specifications described below, our results remain qualitatively the same and stay significant. Table A.6 includes school group-fixed effects and Table A.9 controls for school group-level characteristics (specifically the percentage of students who are female and the mean performance of students in Round 2 of the experiment). The profile choices of students in our sample differ slightly from the national average. To test whether this has an impact on our results, we run weighted ordered probit regressions in Table A.8. As discussed above, the appendix also contains a number of specifications where we treat combi-profile students in different ways. In Table A.10, we treat ES/CS students as ES and NH/NT students as NT. In Table A.11, we treat these profiles as separate (using NT>NT/NH>NH>ES>ES/CS>CS as our ranking). In Table A.12, instead of using our own ranking we use the rank each student herself gave to the profile she picked. Finally, in Tables A.13-A.16, we run binary regressions of choosing NT vs. the rest, Nature vs. Society, CS vs. the rest and own top ranked vs. the rest.

A final control concerns the socio-economic background of students. While we did not collect any socio-economic background data on the students in our sample, we have their first names. Bloothooft and Onland (2011) show that in the Netherlands, names are strongly predictive of social class, income and lifestyle and develop a classification of names into 14 categories. We implement

generates a reduction in the gender gap in study profile choices that is 65 percent of the overall size of the reduction generated by all three psychological attributes. The corresponding number is 70 percent and 110 percent when we either classify combination profiles as separate choices or when we use for each student their own ranking of prestigiousness, respectively. This confirms that the impact of competitiveness is quite distinct from that of confidence or risk attitudes.

[37] We present binary OLS regressions of all results in the online appendix (i.e. for the binary decisions of NT vs. the rest, nature vs. society, rest vs. CS and self-rated best vs. rest).

this classification in our sample and in columns (9) and (10) in Table 7 we control for category dummies and students' relative age (measured in days).[38] Table A.7 in the appendix reports the full table with category dummies and age control.[39] Our main result remains qualitatively the same and remains significant.

6 Discussion and Conclusion

This study has presented evidence showing that an incentivized measure of competitiveness is a relevant predictor of important education choices of young people in the Netherlands, and that a substantial share of gender differences in these education choices can be attributed to gender differences in competitiveness. One might, however, worry that our measure of competitiveness – tournament entry conditional on performance – is actually picking up other traits that influence education choices, such as the students' perceived or actual mathematical ability, or their preference for math. We address each of these concerns.

Concerning tournament entry being an additional measure for perceived math ability, note that when we add entry to ordered probit regressions on study profile choice, the effects of perceived math ability are not substantially altered (compare columns (1) and (2) in Table 7). Furthermore, the guessed rank in the experimental task, which might be an even better additional predictor of the students' perceived math ability, is not correlated with the study profile choice, despite being significantly correlated with the decision to enter the tournament.

To assess whether the decision to enter the tournament is mostly an additional measure of actual math ability, note that all regressions control for performance in the experiment. In addition, when we add entry to ordered probit regressions on study profile choice, the effects of actual math ability are not substantially altered (again compare columns (1) and (2) in Table 7). Furthermore, conditional on subjective math ability the absolute and relative math grades do not significantly predict study profile choice (column (1) in Table 7): absolute and relative math grades are not jointly significant (p=0.39)). The coefficient on tournament entry, however, is both significant and much larger than the coefficient on the standardized math grade. Finally, if anything, the coefficient on GPA slightly increases rather than decreases when we add the entry decision in Table 7.[40]

Finally, the decision to enter the tournament could be a measure of the students' preference or tolerance for math. One channel could be that a preference for math translates to more optimistic beliefs on relative performance in math tasks, which we already discussed. A second possible mechanism is that a preference for math translates into a preference or tolerance for feedback on relative performance or a relative payment scheme. While we have no direct evidence addressing this concern in the present paper, the results of Niederle and Vesterlund (2007) suggest that this is not the case.

[38] Table A.1 in the online appendix lists the 14 categories and their proportions in our sample.

[39] For this analysis, we have to drop another four students for whom we do not have their birth date.

[40] To be precise, in column (3) of Table A.5 in the online appendix we find that a one standard deviation increase in GPA bridges 12.3 percent of the gap between choosing the least and the most prestigious profile (GPA/(Cut3-Cut1)). In column (4), when we add entry, the effect of the GPA is 13.6 percent. Similar results hold for comparing the impact of an increase in the GPA between columns (7) and (8), columns (9) and (10), columns (11) and (12) and columns (13) and (14).

Specifically, they constructed a second choice environment where subjects could receive information about their relative performance and be paid depending on their relative performance without having to compete. Their paper found no gender differences in choices of such a relative payment scheme over a piece rate payment.[41] Overall, we are therefore confident that the choice to enter a tournament is a measure of competitiveness rather than of actual or perceived math performance, or a preference for math.

This paper is part of a small but growing literature that aims to predict economic outcomes outside of the laboratory with laboratory measures, see e.g. Karlan (2005), Ashraf et al. (2006), Fehr and Goette (2007), Meier and Sprenger (2010), Dohmen et al. (2011), Dohmen and Falk (2011), Zhang (2012a). This is a promising and important approach to show the external validity of traits measured in the lab, but more importantly to show their economic significance, that is, confirm their external *relevance*. One main challenge in this line of research is to beware of reverse causality. This would, for example, have been a significant concern had we measured competitiveness after students made their choices and when they all have different classroom experiences. This is why we administer the experiment while students still share the same experiences, several months before they make their education choice.

The paper most closely related to ours that studies the external relevance of competitiveness is Zhang (2012a). She conducts a standard Niederle and Vesterlund (2007) competitiveness experiment with middle schoolers from Ninglang county in China and observes their decision to take a very competitive entry exam for high school. She finds that students more inclined to compete are more likely to take the entry exam, controlling for the test score on a previous exam. The results indicate no large gender difference in either take up rates of the entry exam, or, perhaps more surprisingly, in tournament entry. The latter is in contrast to other studies that found gender differences in competitiveness among children (Sutter and Rützler, 2010), or Zhang (2012b) who finds gender differences for ethnic minorities among high school children from the same area.

A second approach commonly referred to as showing the external validity of laboratory results is to mimic laboratory experiments in a richer and ideally more naturally-occurring field setting. While gender differences in competitiveness have been repeatedly documented in the field, there has only been limited evidence on gender differences in tournament entry (see Niederle and Vesterlund, 2011, for a survey). In a recent study, Flory et al. (2010) conducted a field experiment in which job-seekers were randomly offered compensation schemes that varied in the degree of competition. In accordance with the findings from the laboratory, they find that women are relatively less likely to apply to a job with a competitive payment scheme than men. While it is reassuring that both the intensive and extensive margin of gender differences in competitiveness can be found in additional

[41] Specifically, after performing in a piece rate, then a tournament and then a treatment where subjects chose between those two payment schemes (as in our own experiment), subjects encountered the following choice in the fourth and last round. In case this round was chosen for payment, they were paid according to their round 1 piece rate performance but had to decide how to be paid: either via a piece rate or via a tournament, where the person with the highest round 1 piece rate performance wins. The choice of tournament in this "submit the piece rate" round (which is identical to the round 3 tournament entry choice except for the need to perform and compete) showed no gender difference once the task 1 piece rate performance and beliefs on the relative piece rate performance were controlled for.

specific groups beyond school and college students, such evidence does not directly inform us whether gender differences in competitiveness can account for an economically significant portion of observed gender differences in educational choices and labor market outcomes. That is, while the external validity of laboratory results to other subject pools are confirmed, such studies do not necessarily address the external relevance of the concept to standard economic questions.

By validating the importance of competitiveness, our paper opens up new research questions. For example, how does competitiveness predict the performance of students in various study profiles? One could imagine that competitive students fare better in terms of grades than their less competitive peers. On the other hand, competitiveness may lead students to "overreach" and enter study profiles that are too difficult for them. We saw that especially some boys aim for the most mathematically heavy NT track while scoring high on competitiveness but not so much on the math grade. It will be important to understand the extent to which competitiveness affects the study profile choices of students, and the extent to which it affects the performance of students once they chose certain profiles. If competitiveness mostly affects the choices, this suggests the policy relevant question of whether different choice environments can affect study choices because different choice environments reward different psychological attributes such as competitiveness, see e.g. Niederle and Yestrumskas (2008).

Future research will determine whether our result can be replicated in other environments and with different or larger subject pools. In our environment, prestige and math intensity are very correlated and it remains to be determined whether our results hold when this is not the case. Likewise, it remains to be determined to what extent a competitiveness measure on other, less math oriented tasks, correlates with the present measure and more importantly with study profile choices. Given our results, another important question is what competitiveness exactly measures, and how it is correlated with other traits which may be more familiar but could be hard to capture. For example, how does competitiveness differ from traits like ambition or challenge seeking? Which psychological traits correlate with competitiveness? Finally, an important open question is whether we can manipulate the competitiveness of students and whether this would affect their educational choices.[42]

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[42]Furthermore, it is still far from clear to which extent gender differences in competitiveness are determined by nature and by nurture. Buser (2012) and Wozniak et al. (2010) find that for women the likelihood of entering the tournament varies over the menstrual cycle and Hoffman and Gneezy (2010) find that it is correlated with handedness. On the other hand, Gneezy et al. (2009) find that the gender gap in competitiveness varies between a patriarchal and a matrilineal society and Cardenas et al. (2012) find that gender differences in competitiveness vary across countries and may be correlated with gender stereotypes.

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