Competitiveness, Risk Attitudes and the Gender Gap in Mathematics Achievement*

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Abstract

In this paper, we investigate how competitiveness and risk attitudes are related to mathematics achievement among middle school students. We conduct an experiment at six public middle schools in Japan to collect incentivized measures of competitiveness and risk attitudes and merge them with an administrative dataset containing information on students' cognitive achievements. We find that competitiveness is positively correlated with mathematics achievement conditional on students' prior achievements and demographics, while greater risk aversion is associated with higher mathematics achievement (but not with reading and English). Since girls are less competitive and exhibit greater risk aversion compared to boys, the results indicate that the gender differences in competitiveness are widening the gender gap in mathematics achievement, but that the gender differences in risk attitudes contribute to narrowing it.

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1 Introduction

The gender gap in mathematics achievement has gotten particular attention in economics. This is because that, in contrast to other subjects such as reading, mathematics ability and preparation serve as a good predictor of future labor market outcomes. For example, Joensen and Nielsen (2009, 2016) exploit an institutional reduction in the costs of acquiring advanced high school mathematics in Denmark and provide evidence that choice of a more math-intensive high school specialization has a causal effect on future labor market earnings. It is also thought that mathematical proficiency does not just benefit individuals but also considered crucial to drive economic growth and create innovation.

Although some of the recent data indicate that the gender gap in mathematics achievement is narrowing, we still observe girls performing worse than boys on standardized mathematics examinations in many developed countries. For example, the 2015 Program for International Student Assessment (PISA) finds that boys outperform girls in mathematics by 8 score points on average across OECD countries; Boy's advantage at the mean is statistically significant in 28 countries and economies that participated in PISA (OECD, 2017). In order to consider potential policies that could narrow the gap, gaining a better understanding of how the gender math gap arises is an issue of first-order importance.

The objective of this paper is to investigate how gender-linked psychological traits such as competitiveness and risk attitudes are related to mathematics achievement among middle school students. In doing so, we examine to what extent the gender gap in math is attributable to gender differences in competitiveness and risk attitudes. There is a broad consensus in the experimental literature that women are less competitive and exhibit greater risk aversion as compared to men. These two noncognitive psychological traits may be important in the production of cognitive achievements. As Heckman (2006) argues, noncognitive traits could cause people to endogenously create environments during childhood that foster faster cognitive development. As for competitiveness, for example, students who are more competitive may compete for grades with their peers and improve their cognitive skills through rivalry. Moreover, more competitive students may be willing to enter competitive career (e.g., Buser, Niederle and Oosterbeek, 2014; Almas et al. 2016;

Buser, Peter and Wolter, 2017), and may have higher motivation for learning. On the other hand, since the seminal work by Levhari and Weiss (1974), the link between human capital investment and risk attitudes have gotten particular attention in economics. If future returns to educational investment are uncertain, students who are risk averse may lower educational investment which results in lower achievement. Alternatively, risk attitudes may change the way how students behave in school activities. For example, students who are more risk averse might start doing their homework earlier than the students who are more risk tolerant in order to avoid the risk of not meeting the deadline. In spite of these various potential mechanisms in which competitiveness and risk attitudes affect the production of cognitive achievements, an important question of how these noncognitive psychological traits are related to cognitive achievements are relatively unexplored. Furthermore, if competitiveness and risk attitudes are related to mathematics achievement, it is potentially the case that the gender differences in these traits are related to the gender gap in mathematics achievements.

To this end, we conduct an incentivized experiment at six public middle schools in Japan to collect measures of competitiveness and risk attitudes and merge them with an administrative dataset containing information on students' cognitive achievements. We find that competitiveness is positively correlated with mathematics achievement conditional on students' prior achievements and demographics, while greater risk aversion is associated with higher mathematics achievement (but not with reading and English). Since girls are less competitive and exhibit greater risk aversion compared to boys, the results indicate that the gender differences in competitiveness are widening the gender gap in mathematics achievement, but that the gender differences in risk attitudes contribute to narrowing it.

1.1 Related Literature

First of all, our paper is related to the empirical literature of the production of cognitive achievements (e.g., Todd and Wolpin, 2003; Cunha and Heckman, 2008). In particular, Cunha and Heckman (2008) construct a dynamic structural model in which cognitive and noncognitive skills evolve jointly and estimate its production function parameters. Even though our approach in this paper is not structural, the paper examines how noncognitive psychological attributes such as competitiveness and risk attitudes are related to the production of cognitive achievements. To the best of our knowledge, this is the first paper which tackles such a question.

Second, the paper adds to the growing literature of behavioral economics of education (e.g., Koch, Nafziger, and Nielsen, 2014; Lavecchia, Liu, and Oreopoulos, 2016). Especially, recent literature accumulates mounting evidence showing that competitiveness is predictive of educational outcomes outside the lab. Buser, Niederle and Oosterbeek (2014) investigate whether competitiveness explains academic track choice of middle school students in the Netherlands. They find that competitiveness predicts the choice of math-heavy specializations in high school and the gender gap in specializations is largely accounted for (about 20%) by the gender differences in competitiveness. For high school students, Almas et al. (2016) show that competitiveness correlates with choosing the college track in Norway and Buser, Peter and Wolter (2017) show that competitiveness can explain a significant portion of the gender gap in math-intensive specialization choices in Switzerland. Similarly, Zhang (2013) provides evidence that students who are more inclined to compete are more likely to take a competitive entrance exam for high school in China. Aside from educational choices, recent evidence suggests that competitiveness is predictive of labor market outcomes such as earnings. [1] In contrast to these literature, our focus is on cognitive achievements, especially mathematics, rather than the educational choices such as academic track choice. We will see that competitiveness is positively associated with mathematics achievement, explaining part of the gender gap in math.

Starting from a theoretical work by Lehvari and Weiss (1974), the relationship between risk attitudes and educational outcomes is a long standing problem in economics. Traditional view is that risk aversion is inversely associated with educational outcomes since uncertainty in returns to education depresses educational investment (e.g., Belzil and Leonardi, 2007, Checchi, Fiorio, and Leonardi, 2014). Recent literature in experimental economics complements this view. In Buser, Niederle and Oosterbeek (2014), the authors find that risk attitudes itself is predictive of academic

[1] Reuben, Sapienza and Zingales (2015) link the starting salary and industry choice of MBA students and find that competitive individuals earn 9 % more than their less competitive peers. Furthermore, they find that gender differences in tournament entry account for about 10 % of the gender gap in earnings. See also Reuben, Wiswall and Zafar (2015), Buser, Geijtenbeek and Plug (2015).

track choices. They report that the more risk averse students are less likely to choose more math-heavy specializations in high school and about 16% of the gender gap in track choices can be explained by the gender differences in risk attitudes. Tannenbaum (2012) analyzes a data sample from the Fall 2001 mathematics SAT and finds that women skip significantly more questions than men. He attributes this difference primarily to gender differences in risk aversion since, in SAT, students are penalized for incorrect answers but not for leaving questions blank. He argues that the gender gap in questions skipped can explain up to 40% of the gender gap in SAT scores. Similarly, using an experiment, Baldiga (2013) finds that women answered significantly fewer questions than men when the wrong answer was penalized, but not when there was no penalty. [2] In contrast to the literature which supports the view that risk aversion is negative for educational outcomes, we show that risk aversion is positively related to mathematics achievements.

Finally, the paper adds to the literature on the gender gap in mathematics achievement. A wide range of theories has been proposed to explain the gender gap in math. These theories can be classified into two broad categories: biological theories such as innate differences in spatial ability, brain development, and theories arguing the importance of societal factors such as differential treatment by parents and teachers, stereotypical threat etc (see Halpern et al., 2007 for a survey). Obviously, sorting out the relative importance of biological versus societal explanations is important since these two imply different policy implications. However, the objective of this paper is not to contribute to that discussion. Rather than that, our objective of this paper is to address the validity of the argument that encourages women to "lean-in" (Sandberg, 2013): women should be more competitive and take on more risk. [3] Our results suggest that, at least from the viewpoint of the gender gap in mathematics achievement, encouraging girls to become more risk tolerant do not necessarily contribute to close the gap in math.

The remainder of the paper unfolds as follows. Section 2 describes the data collection and

[2] There is also a recent stream of experimental literature that investigate the relationship between risk attitudes and innate cognitive ability (e.g., Frederick, 2005; Burks et al. 2009; Dohmen et al. 2010; Benjamin, Brown, and Shapiro 2013). These studies suggest that risk aversion is negatively related to cognitive ability. However, Andersson et al. (2016) show that this relationship may be spurious. In their study, they show that by changing the way how risk elicitation tasks are presented, they are able to generate both negative and positive correlations between risk aversion and cognitive ability. They argue that cognitive ability is related to behavior error rather than to risk preferences.

[3] We are inspired by the discussion of Shurchkov and Eckel (2018) on this part. A related question is whether women should "lean-in" to negotiate more (e.g., Exley, Niederle, and Vesterlund. 2016).

experimental procedures. Section 3 presents benchmark analysis and demonstrate the gender gap in mathematics achievement in our sample and show summary statistics of experimental variables. Section 4 analyses the determinants of tournament entry and demonstrate the gender differences in competitiveness. Section 5 is our main results. Section 6 concludes.

2 Background and Data Collection

We invited 8th-grade students of all 6 public middle schools within the same school district, namely Toda city, one of the largest school districts in Saitama prefecture and a large part of the Kanto metropolitan area in Japan. Schools are geographically located within 12 km radius. Approximately two months prior to the experiment (Feb 2 through 13, 2017), the authors directly visited all schools and explained the schedule, setting, and financial incentive of the experiment in detail. Students were distributed a letter about details of the experiment to families and a parental consent form, and were required to return a signed consent form by about two weeks.[4]

After all, we received 848 students' parental consent forms (out of a possible 1080) and finally 811 students (389 male, 422 female) from 30 classes participated in our experiment, which were accounted for 75% out of the entire 8th-grade students.[5] To prevent the detailed information on the experiments from spreading to other schools, we set up the experiments and collected data within three consecutive days, March 21, 22, and 23, 2017.

Students who participated in the experiment received, on average, 1,022JPY (=10USD), with minimum of 500JPY (=5USD) and maximum of 3,400JPY (=34USD), including a fixed participation fee, 500JPY (=5USD). It should be noted that, due to administrative and educational reasons, students were paid by the combination of bookstore gift cards and regular gift cards (called "QUO card" which can be used in many stores, such as convenience stores, drugstores, restaurants, and

[4]However, the students were not informed on the specific task of the experiment at that time to prevent students from self-selecting into the participation in experiments, based on their favorite tasks. The parental consent form included the same information given to the students. Teachers, except for the principle, were not fully informed about the experiments to make sure students did not find out about the purpose of this experiment.

[5]According to the official statistics, the total numbers of 8th-grade students at the beginning of 2016 academic semester was 1108. However, we excluded 28 students from this calculation who (i) students who were absent on the day of the standardized exam; (ii) students who transferred from/to other schools after the day of the standardized exam; and (iii) students who belonged to special education classrooms.

gas stations, etc). Although students were informed that they were paid with gift cards in advance, they left uninformed of how much they were paid with bookstore gift cards or how much regular gift cards. Since either gift cards can be easily cashed at a cash voucher shop or anywhere, it is unlikely that paying in gift cards, not cash, will cause a potential problem for our results. These gift cards were mailed to each student three months after the experiments, although it was later than the initial schedule (one month after the experiment) due to the unexpected accident on the postage.

2.1 Experiment

Each day on March 21, 22 and 23, 2017, the experiment was conducted after school and it took about an hour. Students were randomly assigned to 44 classrooms in 6 schools, ranging in size from 11 to 28 of them each. To prevent copying the answers from neighbors, students were asked to sit in every other seat in the classroom. We, with assistance of two Research Assistants (RAs) per classroom, administered the experiment for about 60 minutes, including the short survey. To see how experimental environments affect individual decision makings, we used a between-subjects 2 $\times$ 2 design and randomly manipulate environments in the classrooms.[6] The environments differed in the visibility of the choices (private vs public), and the experimental peer groups (same-sex vs mixed gender), as explained below.

The visibility of the choices. We randomly assigned students to choose their choices in the experiment in "public" situations or in "private" situations. In the public treatment, students were announced that their choices during the experiment would be made public to the students who were participating in the experiment in the same room by our research assistants at the end of the experiment. In the private treatment, the choices would be kept private throughout the experiment as in the standard literature.

The experimental peer groups. We randomly assigned students to participate in the experiment with same-sex peer groups or mixed-sex peer groups. This treatment concerns the gender composition in the room where the experiments take place. Students were randomly assigned a

[6] We stratified students by school and gender.

room either with same-sex peers or with mixed-sex peers.

These treatments are designed to see how social image concerns as well as the presence of opposite sex peers affect economic decision making among middle school students which is conceptually similar motivation with Bursztyn, Fujiwara and Parrais (2017), Buser, Ranehill and Veldhuizen (2017) and Yagasaki and Morishita (2018). Eventually, however, we see no statistically significant impacts across any treatments. [7]This suggests that our experimental measures such as competitiveness and risk attitudes are robust to these treatments, enabling us to pool the samples in the following analysis.

The experiment basically follows the standard design of Niederle and Vesterlund (2007). The experiment consisted of five rounds, one of which was randomly selected for payment. In the first three rounds, participants were asked to solve as many as possible mazes in three minutes. The experiment was conducted using paper and pencil. An example of maze is shown in Figure 1 below.

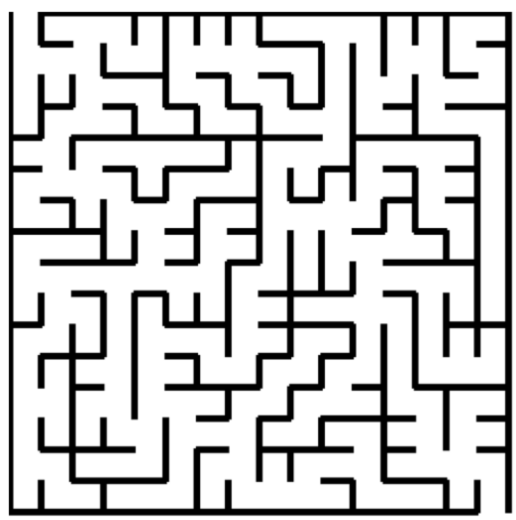

Figure 1: an example of maze

The incentive structure of each round is laid out below.

Round 1: Piece Rate. Students would receive 50 points for each maze correctly solved.

[7]Detailed analysis of this part is under preparation and available upon request.

Round 2: Compulsory Tournament. Students were randomly divided into groups of three, and a student who solved the maze most among the three can obtain 150 points per each but the remaining two could not get any points at all. Students were not informed about who they were assigned into the same group as themselves throughout the experiment. If the number of mazes solved were tied at the first place, the winner were chosen randomly.

Round 3: Choice. Students were asked to choose either piece rate or tournament before performing task. If they were to choose piece rate, they would get 50 points per maze solved correctly. If they were to choose tournament, they would get 150 points per maze solved correctly if there score exceeded that of remaining two of the group members in round 2, otherwise they would receive no payment. In case of ties the winner were chosen randomly.

Round 4: Submitting Piece Rate Performance. No maze task was performed here. Students were asked to choose either piece rate or tournament to apply their round 1 piece rate performance. If they were to choose piece rate, they would receive the same payment as they did in round 1. If they were to choose tournament, they would get 150 points per maze if there round 1 score exceeded that of remaining two of the group members in round 2, otherwise they would receive no payment. In case of ties the winner were chosen randomly.

Round 5: Lottery. Students were asked to pick one option among a sure payoff of 400 points and five 50/50 lotteries: 500 or 350, 600 or 300, 700 or 250, 800 or 200 and 900 or 100 (points). (See Table 1.) For lotteries 1-5, the expected payoff increases linearly with risk, as represented by the standard deviation. Note that lottery 6 has the same expected payoff as lottery 5 but with a higher standard deviation. These lotteries are designed so that higher number of the choice of a lottery implies greater preference for risks.[8] The outcome of the lottery was determined by flipping

[8]The last column in Table 1 represents implied CRRA range corresponding to each chosen lotteries. The intervals are determined by assuming $u(x) = x^{1-r}$ and calculating the value of r that would make the individual indifferent between the lottery s/he chose and the two adjacent lotteries. Theoretically, individuals with $r > 0$ can be classified as risk averse, $r < 0$ as risk loving and $r = 0$ as risk neutral.

Table 1: Lotteries in Round 5

Choice(50/50 lottery)	High	Low	Mean	SD	Implied CRRA range
Lottery 1	400	400	400	0	$3.94 < r$
Lottery 2	500	350	425	75	$1.32 < r < 3.94$
Lottery 3	600	300	450	150	$0.81 < r < 1.32$
Lottery 4	700	250	475	225	$0.57 < r < 0.81$
Lottery 5	800	200	500	300	$0 < r < 0.57$
Lottery 6	900	100	500	400	$r < 0$

a coin at the end of the experiment if this round was randomly chosen for compensation.

In rounds 3, 4 and 5, students in the public treatment were announced that the choice of that round would be made public to the peers in the same room, if it was randomly chosen for compensation, at the end of the experiment. Finally, students answered a detailed questionnaire including questions on confidence, psychological attributes and demographics such as family patterns, parental employment status and the number of siblings. Confidence measures were elicited by asking students to guess their relative rank in round 1 and round 2 performances of their group of three. If their guess were correct, they receive 100 points for each. [9]

2.2 Administrative Data

A few months after the experiment, we obtained several administrative data from the local government and matched with the data collected through the experiment. Firstly, we are allowed to access standardized test scores that the local government of Saitama prefecture administered every academic year. This standardized test, started from 2015, was constructed as panel data, tracking down the same students over time. Therefore, one of the greatest advantages of accessing this dataset is we are able to employ the value-added specifications of the education production

[9]The questionnaire also asks questions on empirical norms. For instance, it asks each student 'what fraction of boys/ girls in your school who participated into the experiment do you think choose tournament in round 2'. If the guess is correct, then the student gets 100 points. These questions are designed to elicit students' belief about their gender stereotype.

function. Education production function is written as a cumulative model as students' cognitive ability that allows test performance at a given age to depend on the historical inputs both from schools and families. It thus requires taking into account input measures accumulated from the past, which are likely to be missing variables. However, due to address the historical input measures, including a lagged IRT score in previous academic year provides sufficient statistics for all historical inputs and students' genetic endowments. As Todd and Wolpin (2003, 2007) suggested, the value-added specification is regarded as being better than the cross-sectional specifications. Secondly, the important feature of this standardized test is employing the Item Response Theory (IRT) in estimating students' academic ability more precisely (for details, see Embretson and Reise, 2000). Contrary to the Classical Test Theory (CCT), the IRT is successful to separate the difficulty level of problems on the test from the difference in students' academic ability. In addition, ability estimates of IRT at different times are mapped in a common scale so that the IRT scores of the same student are comparable across different time periods. An important drawback of IRT, however, is that if a student gets either zero or perfect test score, an ability estimate of IRT diverges to negative or positive infinity. Consequently, for these two cases, IRT fails to yield an ability estimate and the data is coded as some symbol to indicate what has happened. In order to address this censoring issue, we mainly use Tobit model in the following analysis. Finally, even though we are able to control for the historical input measures by using the information on prior cognitive achievements, we still need the information on demographics and the current state of inputs. We address this issue by the following three ways. One, as mentioned, there are some information on demographics such as family patterns, parental employment status and the number of siblings in the questionnaire collected during the experiment. Two, in administering the standardized tests, students are requested to answer a series of questionnaires, including students' information on age in months, and cram school attendance etc. Three, we access the administrative data that the local government of Toda-city collected every year, such as whether students' guardians receives public assistances and the subsidy for school lunch and school supplies, both of which are the proxy of family wealth.

3 Descriptive Analysis

In this section, we describe basic characteristics of the students who participated in the experiment. Descriptive statistics of variables we use in our main analysis are displayed by gender in Table 2. To keep the sample constant, we had to drop 67 students because at least one of these key variables are missing for those students. This leaves us with a sample of 744 students (345 boys, 399 girls).

3.1 The Gender Gap in Mathematics Achievement

Even though our primary focus is on math test score, it is useful to see test scores on reading and English by gender as well. It is widely known that girls traditionally exceeds boys in overall middle school performance. Indeed, as displayed in Table 2, in both 8-th grade and 9-th grade, girls are outperforming boys in reading and English. As suggested by Goldin, Katz and Kuziemko (2006), this may due to the later maturation of boys. Table 3 reports the results of Tobit regressions using 9-th grade IRT scores of each subject as dependent variables. As described above, we use Tobit model to account for the censoring issue due to the use of IRT.[10] Table 3 highlights the gender gap in mathematics achievement. Columns (1) to (3) shows that girls are, on average, better at reading and English compared with boys but not at mathematics. Although the estimated difference is not statistically significant, mathematics achievement of girls are on average lower than boys. When we add additional controls, we see more clear relationship. Columns (4) to (6) additionally controls cognitive achievements in the previous year.[11] The estimated coefficient of the female dummy in column (4) is negative and significant at the 1% level, implying that boys are likely to achieve greater improvement in mathematics than girls. This is not the case in reading and English as shown in columns (5) and (6). In addition to these key independent variables of interest, Column

[10]Most of the results are not sensitive to the normality assumption imposed on Tobit model. As a robustness check, we also implement other estimation methods such as OLS by dropping censored data and censored LAD estimator developed in Powell (1984). The results do not change qualitatively. These results are available upon request.

[11]This value-added specifications include lagged test scores not only in mathematics but also in reading and English. The idea behind the inclusion of the lagged test scores is to control for historical input measures in the process of knowledge acquisition. However, there may be problematic in an inclusion of only the lagged achievement measures in mathematics. If students allocate their resources, such as time and concentration, to maximize the overall cognitive achievements, not a test performance for a particular subject, it is more convincing to control for the prior own achievement outcomes in reading and English as well as mathematics.

(7) to (9) adds students' and family socio-demographic variables, which deemed to affect student achievements and are often controlled in standard education production functions (see a survey presented by Todd and Wolpin, 2003). One of the variables that represent family wealth is a dummy variable that takes one if a students' parents receives either public assistances, or the subsidy for school lunch and school supplies, zero otherwise. Moreover, we also control for family patterns and parental employment status. Family patterns are classified into three type of household; (i) a couple and a child(ren), (ii) single parent and a child(ren) and (iii) other. Parental employment status is expressed as a series of dummy variables that correspond to information on who are engaged on a job in household (father, mother, both, or other). Another important control, which could be regarded as a current input measure, is the dummy variable taking one if a student attends for-profit private cram schools outside of formal education, making very important role for students to prepare for the entrance examination of high schools, zero otherwise. Further, widely known determinants of student achievements, the number of siblings and student's age in month are also included in our estimation. According to columns (7) to (9), the coefficients are quantitatively and qualitatively similar even after controlling for these variables. In the following empirical analysis, we investigate what factors lie behind the gender gap in mathematics achievement observed in column (7) in Table 3.

Table 2: Descriptive Statistics

	Boys			Girls			Difference
	N	Mean	SD	N	Mean	SD	t-test
IRT scores							
9-th grade math	342	1.40	1.06	394	1.30	1.05	
9-th grade reading	345	1.49	1.33	399	1.82	1.24	***
9-th grade English	343	1.01	1.15	396	1.34	1.13	***
8-th grade math	345	0.92	1.07	399	0.84	0.95	
8-th grade reading	345	0.84	1.07	399	1.19	1.02	***
8-th grade English	345	0.16	1.04	399	0.49	0.99	***
Growth in math	342	0.49	0.62	394	0.48	0.64	
Growth in reading	345	0.66	0.93	399	0.63	0.87	
Growth in English	343	0.86	0.61	396	0.86	0.63	
Experimental variables							
Performance (Piece-rate)	345	6.09	1.85	399	5.51	1.78	***
Performance (Tournament)	345	8.23	2.31	399	7.45	2.31	***
Tournament entry (round 3)	345	0.41	0.49	399	0.23	0.42	***
Tournament entry (round 4)	345	0.24	0.43	399	0.15	0.36	***
Guessed rank (round 1)	345	2.06	0.64	399	2.21	0.59	***
Guessed rank (round 2)	345	1.69	0.71	399	1.78	0.73	***
Lottery	345	4.08	1.80	399	3.04	1.61	***
Parental employment status							
Only father is employed	345	0.16	0.37	399	0.16	0.37	
Only mother is employed	345	0.08	0.26	399	0.05	0.21	*
Both	345	0.76	0.43	399	0.78	0.42	
Other	345	0.01	0.09	399	0.02	0.12	
Family patterns							
Nuclear family	345	0.74	0.44	399	0.78	0.42	
Single parent and a child(ren)	345	0.11	0.31	399	0.06	0.24	*
Other	345	0.15	0.36	399	0.16	0.37	
Other controls							
Cram school attendance	345	0.75	0.43	399	0.72	0.45	
Number of siblings	345	1.24	0.82	399	1.29	0.89	
Age in months	345	173.49	3.35	399	173.34	3.43	
Low SES	345	0.16	0.36	399	0.15	0.36	

Notes. The table reports average of variables by gender based on 744 students. The last column reports gender differences in means where the significance levels are from t-test ; * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 3: Gender and Cognitive Achievements

	(1) Math	(2) Reading	(3) English	(4) Math	(5) Reading	(6) English	(7) Math	(8) Reading	(9) English
Female	-0.097	0.310***	0.319***	-0.128***	0.081	0.032	-0.119**	0.087	0.031
	(0.082)	(0.094)	(0.086)	(0.047)	(0.058)	(0.047)	(0.047)	(0.058)	(0.047)
8th-grade math				0.697***	0.360***	0.157***	0.683***	0.356***	0.154***
				(0.035)	(0.042)	(0.034)	(0.035)	(0.042)	(0.034)
8th-grade reading				0.050	0.419***	0.173***	0.054*	0.420***	0.174***
				(0.031)	(0.038)	(0.030)	(0.031)	(0.038)	(0.031)
8th-grade English				0.243***	0.382***	0.750***	0.230***	0.375***	0.751***
				(0.035)	(0.042)	(0.034)	(0.035)	(0.043)	(0.034)
School FE	√	√	√	√	√	√	√	√	√
Individual controls							√	√	√
Observations	744	744	744	744	744	744	744	744	744

Notes. Coefficients are from Tobit regressions using 9-th grade achievements as dependent variables. All specifications include school fixed effects. Individual controls include dummies of low socioeconomic status, dummies of cram school attendance, dummies of family patterns, dummies of parental employment status, age in months and the number of siblings. Robust standard errors in parentheses; * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

3.2 The Gender Differences in Psychological Attributes

Table 2 reports average choices and performance in the experiment by gender. Consistent to most of the literature, we find that boys are significantly more likely to enter the tournament than girls are. In our sample, boys are approximately 18 percentage points more likely to choose tournament in round 3. For round 4, boys are 9 percentage points more likely to choose tournament. We also find that boys are on average better in performing mazes in both round 1 and round 2 and the differences are statistically significant.

Confidence and risk attitudes also follow the previous literature and we find that boys are more confident about their relative performance in both round 1 and round 2 and more risk-seeking than girls. For confidence, in Table 2 we see that both boys and girls guess their relative performance to be higher when it comes to round 2. This may reflect the effect of learning between rounds 1 and 2. For risk attitudes, Table 2 shows that boys choose a more risky lottery than girls on average than girls do and the difference is statistically significant.

In summary, our sample exhibit the standard patterns of gender differences that we observe in most of the literature. However, it is not clear to what extent the gender differences in tournament entry is attributable to the gender differences in ability, confidence and risk attitudes in our sample. Therefore, we move on to the regression analysis in the next section.

Table 4 reports the results of OLS regression of tournament entry in round 3. All specifications include school fixed effects and treatment fixed effects. Column (1) shows that girls are 18 percentage points less likely to enter the tournament than boys, when only controlling for school and treatment fixed effects. Column (2) shows that adding ability related measures such as performance in round 2, the difference in performance between rounds 1 and 2 and 8th-grade cognitive achievements reduce the gender effect by 3.1 percentage points (compare columns (1) and (2)). The reduction is as expected, given the gender differences in the number of mazes correctly solved in our sample. Notably, among 8th-grade cognitive achievements, mathematics is the only subject that significantly predicts tournament entry.

In column (3), we add the guessed ranks of rounds 1 and 2 as measures of confidence. We see that adding confidence measures causes the gender effect to drop slightly from 14.9 to 13.4

percentage points. On the other hand, we see a substantial drop in the gender effect when we add the choice of lottery which is a measure of risk attitudes. Comparing columns (3) and (4), adding the lottery choice in round 5 reduces the coefficient of female dummy by 5.2 percentage points (from 13.4 to 8.2 percentage points). Finally in column (5) and (6) we include the dummy of round 4 choice of tournament entry, hereinafter called "submitting the PR", to control other possible factors that influence tournament entry such as feedback aversion. Although submitting the PR significantly predicts tournament entry in round 3, we see almost no effect on the gender effect. Column (6) adds individual controls. Individual controls include dummies of low socioeconomic status, dummies of cram school attendance, dummies of family patterns, dummies of parental employment status, age in months and the number of siblings. Controlling all variables leaves 8.1 percentage points gender gap in tournament entry which is statistically significant at a 5% level.

Overall, the middle school students in our sample exhibit significant gender differences in competitiveness but the point estimate is relatively small (about 8 percentage points) after controlling ability, confidence and risk attitudes. In particular, we see measures of confidence do not have a large impact on the gender gap in tournament entry, whereas the risk attitudes do eliminate substantial portion of the gender effect. This is in contrast with the literature such as Niederle and Vesterlund (2007) and Buser, Niederle and Oosterbeek (2014) in which authors conclude that significant amount of the gender differences in tournament entry is driven by the gender difference in confidence, whereas the risk attitudes do not have a large impact on the gender differences in tournament entry once controlling for confidence.[12] On the other hand, the results are in line with, for example, Gillen, Snowberg and Yariv (2016) in which authors argue that differences in risk aversion, rather than confidence, account for the gender gap in their study.[13]

[12]See Niederle (2016) for a survey on this line.

[13]See also Balafoutas et al. (2012).

Table 4: Determinants of Tournament Entry

	(1)	(2)	(3)	(4)	(5)	(6)
Female	-0.180***	-0.149***	-0.134***	-0.082**	-0.084**	-0.081**
	(0.034)	(0.036)	(0.036)	(0.036)	(0.035)	(0.036)
T-PR		0.003	0.010	0.011	0.018	0.017
		(0.014)	(0.015)	(0.015)	(0.014)	(0.014)
Tournament		0.037***	0.014	0.013	0.007	0.007
		(0.010)	(0.011)	(0.010)	(0.011)	(0.011)
8th-grade math		0.054**	0.041	0.039	0.040	0.041*
		(0.026)	(0.025)	(0.025)	(0.025)	(0.025)
8th-grade reading		0.027	0.021	0.025	0.028	0.027
		(0.023)	(0.022)	(0.021)	(0.022)	(0.021)
8th-grade English		-0.012	-0.013	-0.008	-0.007	-0.010
		(0.025)	(0.025)	(0.025)	(0.025)	(0.025)
Guessed rank R1			-0.051	-0.050	-0.019	-0.013
			(0.032)	(0.031)	(0.032)	(0.032)
Guessed rank R2			-0.123***	-0.092***	-0.094***	-0.099***
			(0.028)	(0.028)	(0.027)	(0.028)
Lottery				0.059***	0.053***	0.052***
				(0.009)	(0.010)	(0.010)
Submitting the PR					0.148***	0.151***
					(0.052)	(0.052)
School and treatment FE	√	√	√	√	√	√
Individual controls						√
Observations	744	744	744	744	744	744

Notes. Dependent variable: tournament entry dummy of round 3. The table presents coefficients from OLS regressions. All regressions control for school fixed effects and treatment fixed effects. Tournament is performance in the round 2 compulsory tournament. T-PR is the difference in performance between the round 2 tournament and the round 1 piece rates. Submitting the PR is the tournament entry dummy of round 4. Individual controls are dummies of low socioeconomic status, dummies of cram school attendance, dummies of family patterns, dummies of parental employment status, age in months and the number of siblings. Robust standard errors in parentheses; * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

4 Main Results

This section reports our main results of this paper. In Table 5, we estimate different specifications of Tobit model with 9th-grade mathematics achievement as the dependent variable. All specifications include 8th-grade cognitive achievements (which are reported in the table), performance in round 2 of the experiment, the difference in performance between rounds 1 and 2, submitting the PR, school fixed effects, treatment fixed effects and the same set of individual controls as in the previous analysis (which are not reported in the table).

Column (1) shows that girls' mathematics achievement are on average significantly lower than that of boys conditional on prior cognitive achievements.[14] In columns (2) to (9), we add measures of competitiveness, confidence and risk attitudes. The female coefficient remains significantly negative even after controlling additional experimental controls that are considered to be correlated with gender. The magnitude of the coefficients, however, varies across specifications, clarifying which factor brings about the gender gap in mathematics achievement.

Column (2), (4), (6) and (8) show the results of regressions controlling for the dummy of tournament entry. The estimated coefficients of the dummy are positive and statistically significant across all of these specifications. This implies that students who enter the tournament in the experiment are likely to achieve greater improvement in mathematics test score. Even when we include measures of confidence and risk attitudes, the coefficient of the tournament entry is still significant at 5% level in column (8), suggesting that the effect is not due to the impact of risk attitudes and confidence. Therefore, competitiveness is associated with higher mathematics achievement.

Columns (3), (4), (7) and (8) include students' guess of their relative performance in rounds 1 and 2. These variables are meant to capture confidence of students. As in Benabou and Tirole (2002), confidence may play a key role in building up intrinsic motivation. Greater confidence makes students believe in that their effort will be very productive, resulting in higher achievements. Indeed, the estimated coefficients are consistent to this hypothesis. All of the estimated coefficients

[14] The results of column (1) of Table 7 are the same as those of column (7) of Table 5, except we now control for performance in round 2 of the experiment, the difference in performance between rounds 1 and 2, submitting the PR and treatment fixed effects.

of guessed ranks are negative and, in some cases, statistically significant. This means that the students who guessed higher rank in performances of rounds 1 and 2 in the experiment, which reflects students' greater confidence, are likely to have higher mathematics achievement.

The results of regressions that control for risk attitudes are reported in columns (5) to (8). The estimated coefficients of the lottery choice variable are all negative and statistically significant at 5% level for three, out of four, specifications. Since higher number of the choice of a lottery implies greater preference for risks, it follows that students who reveal greater risk aversion in the lottery task achieve greater improvement in mathematics.

Table 5: Gender Effect and Psychological Attributes

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Female	-0.105**	-0.088*	-0.096**	-0.083*	-0.125**	-0.112**	-0.120**	-0.109**
	(0.046)	(0.047)	(0.046)	(0.047)	(0.049)	(0.049)	(0.049)	(0.049)
Entry		0.121**		0.105*		0.146***		0.130**
		(0.054)		(0.055)		(0.055)		(0.056)
Guessed rank R1			-0.023	-0.023			-0.019	-0.018
			(0.043)	(0.043)			(0.043)	(0.043)
Guessed rank R2			-0.076**	-0.063			-0.089**	-0.077*
			(0.039)	(0.039)			(0.039)	(0.039)
Lottery					-0.021	-0.029**	-0.026*	-0.033**
					(0.014)	(0.014)	(0.014)	(0.014)
8th-grade math	0.675***	0.668***	0.667***	0.662***	0.676***	0.669***	0.669***	0.663***
	(0.037)	(0.037)	(0.036)	(0.037)	(0.037)	(0.037)	(0.036)	(0.037)
8th-grade reading	0.053	0.050	0.050	0.048	0.053	0.048	0.049	0.046
	(0.032)	(0.032)	(0.032)	(0.032)	(0.032)	(0.032)	(0.032)	(0.032)
8th-grade English	0.228***	0.229***	0.225***	0.226***	0.227***	0.228***	0.223***	0.225***
	(0.034)	(0.034)	(0.034)	(0.034)	(0.034)	(0.034)	(0.034)	(0.033)
Observations	744	744	744	744	744	744	744	744

Notes. Coefficients are from Tobit regressions using 9-th grade mathematics achievement as a dependent variable. All specifications include performance in round 2 of the experiment, the difference in performance between rounds 1 and 2, submitting the PR, school fixed effects, treatment fixed effects and individual controls. Individual controls include dummies of low socioeconomic status, dummies of cram school attendance, dummies of family patterns, dummies of parental employment status, age in months and the number of siblings. Robust standard errors in parentheses; * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 6: Bootstrap results

	Columns	Difference	Percentage change	p-value
Competitiveness	(1)-(2)	0.017	16. 2%	0.013
	(3)-(4)	0.013	13.5%	0.031
	(5)-(6)	0.013	10.4%	0.011
	(7)-(8)	0.011	9.2%	0.023
Risk attitudes	(1)-(5)	-0.020	-19.0%	0.066
	(2)-(6)	-0.024	-27.3%	0.018
	(3)-(7)	-0.016	-16.7%	0.027
	(4)-(8)	-0.026	-31.3%	0.011
Confidence	(1)-(3)	0.009	8.6%	0.050
	(2)-(4)	0.005	5.7%	0.125
	(5)-(7)	0.005	4.0%	0.199
	(6)-(8)	0.003	2.7%	0.292
Competitiveness+Risk attitudes	(1)-(6)	-0.007	-6.7%	0.328
	(3)-(8)	-0.013	-13.5%	0.189
Competitiveness+Risk attitudes+Confidence	(1)-(8)	-0.004	-3.8%	0.411

Notes. This table reports the results of bootstrap for the reduction in the female coefficient upon controlling for competitiveness, risk attitudes and confidence with 10,000 repetitions. p-value is equal to the number of repetitions divided by 10,000 in which the reduction points toward the opposite direction.

4.1 Effects on the Gender Gap in Mathematics Achievement

To assess the roles of competitiveness, risk attitudes and confidence in accounting for the gender gap in mathematics achievement, Table 6 reports the results of bootstrap for the reduction in the female coefficient upon controlling for those variables. For competitiveness, the reductions in the female coefficient are all statistically significant at 5% level. The results show that the gender differences in competitiveness account for 9.2% to 16.2% of the gender gap in mathematics achievement. In other words, the gender differences in competitiveness is widening the gender gap in mathematics achievements. Risk attitudes are in contrast to competitiveness. Since girls are more likely to be risk averse and greater risk aversion is associated with higher mathematics achievements, controlling risk attitudes increase the female coefficient by 19.0% to 31.3%. The magnitudes are statistically significant at 5% level for three out of four specifications. This means that the gender differences in risk attitudes contribute to narrowing the gender gap in mathematics achievements. We also report the results of confidence. Greater confidence is associated with higher achievements and boys are likely to be more confident than girls. Indeed, controlling for confidence results in 2.7% to 8.6% reduction in the female coefficient. However, three out of four specifications, the reductions are not statistically significant. Finally, we investigate the relative impacts of controlling competitiveness and risk attitudes. The bottom three rows report the reduction in the female coefficient upon controlling competitiveness and risk attitudes (and confidence) simultaneously. Although the differences are all negative, which suggests that the impact of controlling risk attitudes is slightly stronger, we see no statistically significant impacts for any of the specifications. Thus competitiveness and risk attitudes taken together do almost nothing to explain the gender gap in math in our study.

Table 7: Cognitive Achievements and Psychological Attributes

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
		Math			Reading			English	
	Full	Boys	Girls	Full	Boys	Girls	Full	Boys	Girls
Female	-0.109**			0.085			0.046		
	(0.049)			(0.058)			(0.049)		
Entry	0.130**	0.120*	0.157*	0.043	-0.044	0.156*	0.026	0.055	0.016
	(0.056)	(0.071)	(0.090)	(0.063)	(0.091)	(0.089)	(0.055)	(0.074)	(0.086)
Guessed rank R1	-0.018	-0.068	0.001	-0.062	-0.153*	0.062	-0.044	-0.067	-0.055
	(0.043)	(0.057)	(0.069)	(0.057)	(0.082)	(0.075)	(0.047)	(0.064)	(0.074)
Guessed rank R2	-0.077*	-0.048	-0.093	-0.031	0.035	-0.080	-0.027	-0.040	0.004
	(0.039)	(0.054)	(0.057)	(0.054)	(0.086)	(0.066)	(0.039)	(0.058)	(0.053)
Lottery	-0.033**	-0.038**	-0.037*	-0.020	-0.034	-0.000	0.001	-0.017	0.014
	(0.014)	(0.019)	(0.022)	(0.016)	(0.023)	(0.026)	(0.014)	(0.019)	(0.022)
8th-grade math	0.663***	0.597***	0.727***	0.343***	0.278***	0.380***	0.145***	0.062	0.233***
	(0.037)	(0.051)	(0.052)	(0.044)	(0.063)	(0.059)	(0.035)	(0.051)	(0.048)
8th-grade reading	0.046	0.079*	0.017	0.414***	0.395***	0.439***	0.171***	0.216***	0.142***
	(0.032)	(0.047)	(0.043)	(0.040)	(0.062)	(0.051)	(0.032)	(0.046)	(0.044)
8th-grade English	0.225***	0.244***	0.203***	0.378***	0.460***	0.313***	0.752***	0.768***	0.729***
	(0.033)	(0.046)	(0.047)	(0.048)	(0.069)	(0.061)	(0.037)	(0.052)	(0.050)
Observations	744	345	399	744	345	399	744	345	399

Notes. Coefficients are from Tobit regressions using 9-th grade achievements as dependent variables. All specifications include performance in round 2 of the experiment, the difference in performance between rounds 1 and 2, submitting the PR, school fixed effects, treatment fixed effects and individual controls. Robust standard errors in parentheses; * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

4.2 Subsample Analysis

Columns (1) to (3) of Table 7 report the results of regressions using mathematics achievement as a dependent variable. The results of column (1) are the same as those of column (8) of Table 5. Columns (2) and (3) report the results of subsample analysis by gender. For both boys and girls, the coefficients on the dummy of tournament entry and the lottery choice are significant and the results are quantitatively similar across gender. Therefore, we conclude that the results are stable across gender and competitiveness and greater risk aversion are associated with higher mathematics achievement.

4.3 Effects on Reading and English

Columns (4) to (6) report the results for reading achievement and columns (7) to (9) are those for English achievement. The estimated coefficients on the dummy of tournament entry and the lottery choice in these regressions are insignificant except for the coefficient of tournament entry on reading achievement in girls sample. Overall, the results for reading and English achievements are unstable across gender and inconclusive.

5 Conclusion

In order to design useful policies that could narrow the gender math gap, determining how these differences arise is an issue of first-order importance. The aim of this paper is to investigate whether gender differences in competitiveness and risk attitudes explain the gender gap in mathematics achievement. We conduct an incentivized experiment at six public middle schools in Japan and collect measures of competitiveness and risk attitudes and merge them with an administrative dataset containing information on students' cognitive achievements. We find that competitiveness is positively correlated with mathematics achievement conditional on students' prior achievements and demographics, while greater risk aversion is associated with higher mathematics achievement. Since girls are less competitive and exhibit greater risk aversion compared to boys, the results indicate that gender differences in competitiveness is widening the gender gap in mathematics achievement, but the gender differences in risk attitudes contribute to narrowing it.

Our findings suggest that government policies hoping to encourage girls to "lean in" (Sandberg, 2013) - girls should be more competitive, and take on more risk etc - do not necessarily contribute to close the gender gap at least in mathematics achievement. Indeed, controlling competitiveness and risk attitudes simultaneously does not have a significant impact on the gender gap in math in our study (see Table 6). We see substantial gender math gap remains after we control experimental measures and individual controls and thus further research is definitely needed to uncover sources that derive the gap.

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