Overconfidence and Preferences for Competition

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ABSTRACT

We study when preferences for competition are a positive economic trait among high earners and the extent to which this trait can explain the gender gap in income among MBAs. Consistent with the experimental evidence, preferences for competition are a positive economic trait only for individuals who are not overconfident. Preferences for competition correlate with income only at graduation when bonuses are guaranteed and not a function of performance. Overconfident competition-loving MBAs observe lower compensation and income growth, and experience greater exit from high-reward industries and more frequent job interruptions. Preferences for competition do not explain the gender pay gap among MBAs.

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Academic research has documented a significant gender gap in top managerial compensation, with this gap even larger than for regular jobs (Bertrand and Hallock, 2001; Kulich et al., 2011; Blau and Kahn, 2017). One possible explanation for this gap is the fact that, as Niederle and Vesterlund (2007) document, women shy away from competitive tournaments.[1] This hypothesis finds support in recent papers that use Niederle and Vesterlund's measure to study subsequent life choices and outcomes, such as high school students' educational choices (e.g., Buser et al., 2014) and income in the general population (Buser et al., 2020). These studies find that preferences for competition boost positive economic outcomes.[2] The cumulative evidence is sufficiently strong that Balafoutas et al. (2018) propose the use of priming to eliminate the gender difference in the willingness to compete and generate more gender balanced outcomes in labor markets.

In Niederle and Vesterlund's (2007) original lab experiment, however, preferences for competition are not necessarily conducive to better economic outcomes. In particular, a risk-neutral individual participating in the experiment is better off choosing the tournament only if they belong to the top 37% of the skill distribution. Of the 53% of men who chose to compete, 30% earned less because of that choice. Thus, a preference for competition is not unequivocally a good trait: overconfident people who compete when they should not end up earning less. Whether this result carries over to the field, particularly in jobs where pay is strongly linked to performance remains an open question.

In this paper, we investigate whether preferences for competition are a positive economic trait among high earners and the extent to which this trait can explain the gender gap in income. We focus on a sample of individuals who obtained a master's degree in business administration (MBA) from a top-ranked U.S. business school. This highly selected sample has the advantage of targeting high-earning individuals with high pay-for-performance. We have data on earnings for our MBA sample at two points in time: at graduation, when earnings are unrelated to job performance, and seven years later, when earnings are based on job performance.[3] By comparing the effect of preferences for competition at these two points in time, we can uncover the potential mechanism through which these preferences impact earnings and how this relationship changes over time.

[1]For reviews of the experimental findings, see Niederle and Vesterlund (2011) and Dariel et al. (2017).

[2]The analysis of Buser et al. (2014) has been replicated in Switzerland (Buser et al., 2017, 2022) and the United States (Reuben et al., 2017; Kamas and Preston, 2018) for major choice among undergraduate students. Fallucchi et al. (2020) report that preferences for competition predict the choice to play professional sports. Zhang (2019) finds that the willingness to compete predicts whether middle school students in rural China take a highly demanding high school entrance exam.

[3]In our sample, MBAs report the minimum guaranteed bonus for the first year of their job at graduation. Employers offer a minimum guaranteed bonus because MBAs start their jobs in the middle of the year.

Thanks to an extensive data collection effort, we have incentivized measures of individual traits, including preferences for competition and overconfidence. These traits were measured when participants entered the MBA program, 18 months before the first job decision. To capture preferences for competition, we use the experimental design of Niederle and Vesterlund (2007), which consists of giving participants the opportunity to earn money by answering simple arithmetic problems under two different incentive schemes: piece rate and tournament.[4] With piece-rate pay, participants do not compete with others and earn $4 per correct answer. With tournament pay, participants compete with three others and earn $16 per correct answer if they have the highest performance in their group and $0 otherwise. Participants' preferences for competition are assessed by letting them choose between performing under piece-rate or tournament incentives after controlling for their performance, risk preferences, and degree of overconfidence. As in the original experiment, we find gender differences in overconfidence and preferences for competition.

We start by studying the relationship between preferences for competition and income at graduation. We find that the earnings of individuals who chose to compete are 9% higher than those who did not (around $14.6k more per year), with gender differences in preferences for competition accounting for around one-tenth of the gender gap in earnings.[5] Earnings at graduation consist of three components: base salary, one-off bonuses (e.g., relocation and tuition benefits), and guaranteed performance bonuses. The difference in base salaries between MBAs who like to compete and those who do not is economically and statistically negligible, as is the gender difference. By contrast, preferences for competition are significantly correlated with differences in guaranteed performance bonuses. Overconfidence plays no role in explaining salaries at graduation.

Because salaries at graduation are set before the students are hired, none of the income components are based on actual performance on the job. Therefore, the correlation between income and preferences for competition is not due to competition-loving individuals delivering higher performance, albeit we cannot exclude the possibility that employers might have offered higher salaries in expectation of higher performance.

In our data, there are two industries in which salaries are higher, pay-for-performance sensitivity

[4]We elicit preferences for competition using a task in an area (math) typically associated with men (Reuben et al., 2014; Bohnet et al., 2016). Experiments using this task in various subject pools consistently show that men choose the tournament more often than women (e.g., Niederle and Vesterlund, 2007; Cason et al., 2010; Healy and Pate, 2011; Balafoutas and Sutter, 2012; Niederle et al., 2013). That being said, gender differences in preferences for competition are still present but sometimes diminished when measured with stereotypical female tasks (e.g., Kamas and Preston, 2012; Dreber et al., 2014; Wozniak et al., 2014).

[5]Women earn 11% less than men at graduation (around $18.6K). It is worth noting that the experimental measure of preferences for competition is not strongly correlated with the large set of control variables and thus accounts for variance in earnings and the gender gap that would otherwise remain unexplained.

is greater, and promotions tend to occur through an up-or-out system. These industries are finance and consulting. For this reason, we divide the sample into “high-reward” industries (finance and consulting) and the rest. At graduation, there is a strong correlation between preferences for competition and industry choice, with competition-loving individuals 14 percentage points more likely to be hired in a high-reward industry at graduation. Gender and overconfidence do not predict industry choice.

We further study the relationship between these traits and realized income seven years after graduation. We do not find that preferences for competition alone predict income or industry choice. Rather, we find that risk aversion and overconfidence negatively correlate with income. By contrast, we observe a dramatic widening of the gender gap (from 11% to 39%), two-fifths of which is due to differences in industry choice. Controlling for preferences for competition no longer helps explain any percentage of the gender gap.

These divergent trends over time raise three questions. In particular, why do preferences for competition predict income at graduation but not seven years later, why do other traits (overconfidence and risk aversion) become significant, and what drives the widening of the gender gap during the seven years following graduation?

To address these questions, we build on the insight of the original Niederle and Vesterlund (2007) experiment that participants benefit from competing only part of the time. Specifically, participants who mistakenly believe they will outperform others and choose the tournament earn less. Thus, preferences for competition are detrimental to overconfident individuals. Consistent with this result, we find that the interaction between overconfidence and preferences for competition has a strongly negative and statistically significant effect on realized income seven years after graduation. The effect concentrates mainly on the realized bonus component and is robust to controlling for industry fixed effects. Seven years after graduation, competition-loving MBAs with an average level of overconfidence make no more or less than competition-disliking MBAs. However, competition-loving MBAs whose overconfidence is one standard deviation below the mean make \$76k more, while those whose overconfidence is one standard deviation above the mean make \$36k less.

When income and career paths are based largely on performance, as they are in our sample seven years after graduation, employees who underperform will experience lower income growth, be weeded out from high-reward industries, and experience more frequent career interruptions (an indication of potential firings). Overconfident MBAs, particularly those who love competition, are likely to underperform. We therefore expect the interaction between overconfidence and a preference for competition to be significantly associated with lower income growth after graduation, a higher probability of exiting high-reward industries, and a higher probability of career interruptions longer than six months. We find evidence for all three of these effects.

In sum, in high-pay-for-performance jobs, preferences for competition are a positive trait only when they are not associated with overconfidence. This interaction explains why preferences for competition do not explain the gender gap in income among high earners seven years after graduation. Not only do they not have a direct effect (the effect is statistically nil), but they do not even have an effect when interacted with overconfidence, since men have the largest combination of high overconfidence and preferences for competition and this interaction negatively affects compensation.

Our paper contributes to the literature in several ways. We focus on the sample of high earners, a population that is typically compensated based on realized performance. By providing a time dimension, we test whether preferences for competition matter over time and compare a situation in which income is based on performance to one in which it is not. Our findings point in the direction that another result from the lab transfers to the field: preferences for competition are beneficial only when a person is not overconfident. Interestingly, this effect does not hold when compensation is not based on performance.

The paper closest to ours is a contemporaneous study by Buser et al. (2020), who use survey data from the Netherlands and document a positive correlation between preferences for competition and income.[6] Since their competition measure is contemporary with the income measure, they cannot rule out possible reverse causation: individuals who succeed in highly paid jobs are galvanized by their success and become more willing to compete. Moreover, their sample relies less on performance-based compensation as it is a representative sample of the Netherlands, where mean gross income is only $35k (the mean income in our sample is more than five times this amount at graduation and almost 10 times larger seven years later). Our paper, meanwhile, is the only one to study high earners and income at two points in time. Finally, our paper is the first to test an important prediction of Niederle and Vesterlund's (2007) original lab experiment. Namely, that the effect of preferences for competition is modulated by overconfidence.

The rest of the paper is organized as follows. Section I describes the various sources from which we collect our data. Section II presents our sample's descriptive statistics, including gender differences in preferences for competition and income. Section III explores the association between preferences for competition and earnings in the lab. Sections IV and V test the relationship between preferences for competition and income in 2008 and 2015. We discuss potential mechanisms for our findings in Section VI. Finally, we conclude in Section VII.

[6]Other papers in the literature are described in footnote 2. For a survey, see Lozano et al. (2023).

I. Study Design

Our sample consists of the 2008 MBA cohort at the University of Chicago Booth School of Business. We rely on multiple sources of data for this specific cohort: an experiment and an initial survey conducted at the start of their MBA program (in 2006), the school's administrative data, and a follow-up survey conducted seven years after graduation (in 2015).

A. Initial Survey and Experiment

As part of a required core class, all MBA students of the 2008 cohort completed a survey and participated in an experiment designed to measure several individual-specific characteristics. We conducted the survey and the experiment in the fall of 2006, during their first month in the MBA program. Participants completed the survey online before they took part in the experiment. The survey included questions on demographic characteristics and standard questionnaires on personality traits.

The experiment consisted of eight distinct parts. Participants were given instructions for each part before starting the respective part. They did not receive feedback concerning the outcome or behavior of others until the experiment had concluded. As compensation, participants received a $20 show-up fee and their earnings in a randomly selected part. On average, participants earned $99 for the 90-minute experiment. In the Internet Appendix,[7] we provide a detailed description of the procedures used to conduct the survey and experiment, as well as the instructions for the tasks used to measure preferences for competition (materials for the other parts of the survey and experiment are found in Reuben et al., 2008).

To measure preferences for competition, we use a variation of the design used by Niederle and Vesterlund (2007). Participants first performed an adding task under both a tournament payment scheme and a piece-rate payment scheme. They then performed the task again under the payment scheme of their choice. Their payment-scheme choice serves as the basis for classifying their preferences for competition.

The adding task consisted of computing sums of four two-digit numbers for 150 seconds. The computer randomly drew two-digit numbers using a uniform distribution. After each answer, a new set of numbers appeared on the computer screen, along with a message indicating whether their answer was correct or incorrect. Importantly, although participants knew their performance, they

[7] The Internet Appendix is available in the online version of the article on the *Journal of Finance* website and the authors' websites.

did not receive any information about the performance or choices of others during the experiment.

We informed participants that this part of the experiment consisted of four periods, one of which would be randomly chosen to determine their earnings. We also informed them that we randomly assigned them to groups of four.[8] Participants read the instructions for each period just before the start of the respective period. In the first two periods, participants performed the addition task once under the piece-rate payment scheme and once under the tournament payment scheme. Under the piece-rate scheme, participants earned \$4 for every correct answer. Under the tournament scheme, participants earned \$16 for every correct answer if they had the highest number of correct answers in their group (ties were broken randomly) and \$0 otherwise. Half the participants performed the addition task first under piece rate and then under tournament, while the other half performed the tasks in reverse order.

In the third period, we informed participants that they would perform the additions task again and asked them to choose one of the two payment schemes to apply. Participants who chose the piece-rate payment scheme earned \$4 per correct answer. Participants who chose the tournament scheme, earned \$16 per correct answer if they had more correct answers than their other group members when they previously performed the task under the tournament payment scheme. Competing against their group members' past performance has the advantage that the participants' choices and effort in the third period are not affected by other group members' (expected) choices. The variable *competitive* is a dummy variable equal to one if an individual chooses tournament pay in this period.[9]

There are several reasons why participants may prefer a tournament payment scheme. First, they might correctly anticipate that they are a superior performer. Second, they might misperceive their performance and believe they are a superior performer when they are not. Third, they might love risk. Fourth, they might receive a special thrill from performing in a tournament. Following

[8]To avoid group composition effects (e.g., Gneezy et al., 2003), participants in Niederle and Vesterlund (2007) could see that their group consisted of 50% men. Given the fraction of women in our participant pool (30%), we used random assignment to groups without informing participants with whom they were matched. We ran sessions of over 150 participants, and thus, participants could not know their group's gender composition. As expected, the number of women in a group does not correlate with performance or the choice of payment scheme ($p > 0.586$ for men and $p > 0.264$ for women). It also does not correlate with income in 2008 or 2015 ($p > 0.512$ for men and $p > 0.619$ for women).

[9]There was a fourth period in which participants did not perform the adding task. In this period they simply chose whether they wanted their earnings in the fourth period to be calculated based on their past performance and either the piece-rate or the tournament payment scheme. Thus, participants' choice in the fourth period resembled their choice in the third period, except that participants who chose the tournament did not perform under the stress (or thrill) of a competitive environment. The variable *noncompetitive tournament* is a dummy variable equal to one when an individual chooses tournament pay in this period.

Niederle and Vesterlund (2007), we isolate these four components. For this purpose, we need measures of performance, overconfidence, and risk aversion.

To measure individual performance, we compute participants' average rank in the first and second periods. For this variable to not depend on the specific group matching in the experiment, we use the number of sums solved by the participants and simulate one million matches to obtain an average rank for each participant. Since average ranks are higher when performance is lower, for ease of interpretation we define the variable *performance* as the negative of the average ranks.[10]

After the fourth period, we elicited participants' beliefs concerning their relative performance by asking them to guess how they ranked within their group in each of the first two periods. Participants submitted ranks between first and fourth and received $2 for each correct guess.[11] We use the participants' estimated ranks and actual performance to calculate their overconfidence. Specifically, the variable *overconfidence* is the difference between an individual's average rank in the first two periods and their expected rank. Note that since a lower rank means higher performance, this variable is larger when participants overestimate their performance.

B. Administrative Data

The admission office of the business school supplied us the gender variable. The business school's career services office provided us information regarding the job that participants accepted upon graduation. Participants report this information to the career services office following specific instructions on how to report salaries and bonuses. The career services office subsequently double-checks this information with the respective employers to ensure its accuracy. The information include data on earnings, including salaries and yearly and one-off bonuses (e.g., sign-on, relocation, tuition, and retention at year-end bonuses). In cases in which offers include an upper and lower range for a bonus, students are required to report the minimum (guaranteed) bonus. Based on this information, we calculate participants' total earnings in their first year after graduation. We also receive from the career services office self-reported information about the participants, including whether they obtained competing job offers. Because all of these income components are set in advance, and bonuses are based on the minimum guaranteed bonus, our measure of income in 2008 is based only on expected performance, not realized performance.

[10] Many studies in the literature use the number of correct answers as the measure of performance. We use participants' rank for two reasons. First, rank is more relevant to the decision to choose tournament pay. Second, using ranks allows us to easily compare performance and expected performance, which is elicited in ranks.

[11] In the case of a tie, participants were paid the $2 if their guess corresponded to a rank they could have received when the tie was randomly resolved.

C. The 2015 Follow-Up Survey

At the end of 2015, we contacted the same MBAs with a follow-up survey. The survey contained questions about their career, work-life balance, and life satisfaction. More importantly, we asked them about their salary and realized end-of-year bonuses in 2014. Of the 409 original students who consented to the analysis of their data, 263 (64.3%) answered the follow-up survey.

II. Descriptive Statistics

Although participation in the study was mandatory, participants could opt out by not consenting to the use of some or all of their data. Of the 550 students in the cohort, 409 (74%) provided information about their job in 2008 and consented to the analysis of the initial survey, experiment, and administrative data. Note that the decision to consent, even for the job placement data, was made in September 2006, two years before the student graduated. We concentrate on these participants throughout the paper. It is important, however, to understand whether this sample differs systematically from the rest of the cohort. Accordingly, in the Internet Appendix we thoroughly compare the 409 participants in the sample and 129 participants for whom we can analyze data sources other than their job placement data.[12] By and large, we do not find differences between these two populations (see Table IAI in the Internet Appendix). Crucially for this paper, neither the fraction of women nor the fraction of participants who chose the tournament is significantly different (χ^2 tests, $p > 0.388$).[13] Similarly, to understand selection into the sample who responded to the 2015 follow-up survey, in Table IAII of the Internet Appendix we compare the characteristics of the 263 respondents and the 146 non-respondents who had consented to the analysis of their data. The results show that 2015 respondents are positively selected on measures of career success. Nonrespondents are more likely to have lower salaries in 2008, more likely to be women, and more likely to be overconfident, all of which correlate negatively with income in 2015. We discuss potential implications of this selection on our results below.

We next provide descriptive statistics for participants in our sample and evaluate gender differences in the experimental, initial survey, and administrative data. Table I presents the mean and

[12] Of these 129 participants, we have income data for 26 participants who did not consent to the use of their job placement data and 36 who had job offers that were not reviewed by the school's career services office. For the remaining 67 participants, it is unclear whether they failed to report their job placement to the university or whether they did not have a job offer at graduation.

[13] It is also the case that neither the fraction of men nor the fraction of women who chose the tournament significantly differ between the two populations (χ^2 tests, $p > 0.704$).

Table I. Summary Statistics by Gender

This table reports means, standard deviations, and the number of observations for variables used in the paper. The rightmost column displays p-values from tests of the equality of distributions between men and women (t-tests for ordinal variables and χ^2 tests for categorical variables).

	Men			Women			
	mean	*s.d.*	*N*	*mean*	*s.d.*	*N*	$p-value$
Experiment							
Competitive	0.60	0.49	286	0.33	0.47	123	0.000
Performance	2.39	0.78	286	2.70	0.73	123	0.000
Expected rank in adding tasks	2.11	0.76	286	2.54	0.71	123	0.000
Expected experimental earnings	80.38	63.84	286	58.64	35.39	123	0.000
Overconfidence	0.28	0.63	286	0.16	0.65	123	0.095
Risk aversion coefficient	4.22	4.19	286	5.94	4.69	123	0.001
Noncompetitive tournament	0.47	0.50	286	0.25	0.44	123	0.000
Jobs data in 2008							
Total income	185.84	183.12	286	149.22	36.95	123	0.001
Base salary	107.71	18.88	286	105.91	15.68	123	0.318
Total bonus	78.12	176.26	286	43.31	28.45	123	0.001
One-off bonus	44.16	30.46	286	34.91	22.51	123	0.001
Guaranteed performance bonus	33.96	168.98	286	8.40	17.33	123	0.012
Working in finance	0.58	0.49	286	0.36	0.48	123	0.000
Working in consulting	0.20	0.40	286	0.34	0.48	123	0.003
Jobs data in 2015							
Total income	346.93	231.91	189	228.87	180.59	61	0.000
Base salary	194.04	108.58	189	160.22	60.18	61	0.002
Performance bonus	152.89	185.70	189	68.66	143.69	61	0.000
Working in finance	0.48	0.50	189	0.18	0.39	61	0.000
Working in consulting	0.09	0.29	189	0.21	0.41	61	0.010
Number of jobs	2.20	1.04	193	2.27	0.92	70	0.575
Number of promotions	2.41	1.10	193	2.39	1.38	70	0.897
Hours worked per week	54.07	10.01	193	49.57	11.38	70	0.004
Had a career interruption	0.14	0.35	189	0.20	0.40	61	0.263

standard deviation for variables derived from these data sources for the sample's 286 men and 123 women. The table also displays p-values from tests of equality of distributions between men and women based on t-tests for ordinal variables and χ^2 tests for categorical variables. In the experiment and initial survey, we replicate many of the gender differences reported in the experimental literature (Croson and Gneezy, 2009).

A. Gender Differences in Preferences for Competition

Consistent with the literature on preferences for competition, Table I shows that 60% of men choose the tournament payment scheme compared to 33% of women. However, the higher incidence of men choosing the tournament is not enough in and of itself to conclude that men like to compete more. Table I also reveals that men in our sample outperform women in the adding tasks (the average rank is 2.39 for men and 2.70 for women) and tend to be more overconfident than women (on average, men overestimate their rank by 0.28 versus 0.16 by women). Together with the fact that women are more risk-averse, these differences could explain why men choose the tournament more often than women.

Do male MBAs like competition more than female MBAs after controlling for their ability, beliefs, and risk preferences? To address this question, we follow Buser et al. (2014) and run a series of probit regressions with participants' tournament choice as the dependent variable. We report the resulting marginal effects in Table II. In column (1), the only independent variable is participants' gender. Without any controls, the gender gap in choosing the tournament equals 27%. In column (2) we control for participants' performance, which reduces the gender gap in choosing the tournament to 22%. In column (3) we further control for participants' beliefs and risk preferences by including the overconfidence variable and their risk-aversion coefficient. Performance, beliefs, and risk preferences are all significant determinants of tournament choice. However, controlling for these variables still leaves a statistically significant gender gap of 15% in the decision to compete. The gender dummy's coefficient, after controlling for performance, beliefs, and risk preferences, can be interpreted as a gender difference in preferences for competition.[14]

B. Income in 2008

The business school's career office collects data on the base salary and bonuses of all its graduating MBA students. For our analysis, we first consider total income, the sum of base salary and bonuses. In 2008, male MBAs received on average a total income of $186K, which is 25% higher than their female graduates ($149K). Table I also reports separate sample statistics for base salary and bonus pay. We group the various bonuses into one-off bonuses (relocation, tuition, sign-on, and retention at year-end) and the rest, which are guaranteed bonuses related to the performance

[14]This way of testing gender differences in preferences for competition has recently come under scrutiny because measurement error in the control variables or an incorrectly specified regression can result in overestimation of gender differences (Gillen et al., 2019; van Veldhuizen, 2022). In the Internet Appendix, we run a series of robustness checks to test whether this result is susceptible to this problem (see Tables IA.III to IA.V). We do not find evidence that it is.

Table II. Determinants of Willingness to Compete

This table presents regressions of the decision to enter the tournament in the third period of the experiment. Marginal effects from probit regressions are reported with standard errors in parentheses. Performance, overconfidence, and risk aversion are standardized to have a mean of zero and a standard deviation of one. ***, **, and * indicate statistical significance at the 0.01, 0.05, and 0.10 level, respectively.

	(1)	(2)	(3)
Woman	−0.268***	−0.223***	−0.148**
	(0.051)	(0.055)	(0.060)
Performance		0.165***	0.272***
		(0.027)	(0.034)
Overconfidence			0.203***
			(0.033)
Risk aversion			−0.083***
			(0.028)
Obs.	409	409	409
χ^2 test	24.455	57.014	97.111

of the new hires (stock options, profit sharing, guaranteed performance, and other). We refer to the latter component as the "guaranteed performance bonus" for two reasons. First, firms offer these bonuses before the MBAs begin to work. Second, the career office requires students to report the lowest value in the range offered (if a range is quoted). The descriptive statistics reveal that the gender differences concentrate primarily in the bonus, not the base salary. For example, men's average bonus pay is 80% higher than women's. The difference is even more stark in the guaranteed performance bonus component, where men's bonus pay is 404% higher than women's.[15]

The large gender gap in total income is due in part to three male outliers, with salaries above $1M. If we ignore those observations, the average total income of men drops to $170K, the gender gap is reduced to 14%, and the average overall bonus pay for men is 44% higher than that of women (222% higher in the guaranteed performance bonus component).

C. Income in 2015

Our 2015 follow-up survey asks for MBAs' current salary and the year-end performance bonus they received the previous year. We compute total income as the sum of the two. We refer to this income

[15] One possible explanation for the fact that the gender difference is concentrated in the bonus component is that base salaries are more easily measured, and pressure for equality leads to more equal pay in the more visible component. An alternative explanation is that men overstate their bonus rather than follow the instructions of the career services office to report the minimum amount in the range. We discuss this possibility below.

as 2015 income, even if it is technically the sum of the 2015 salary and 2014 realized bonus.

On average, women make \$229K and men \$347K (52% more). Unlike in 2008, in 2015 men's average base salary is significantly higher than the base salary of women by a factor of 1.21. However, the largest difference is again in the bonuses, with men's bonuses larger than women's by a factor of 2.23. Eliminating outliers does not change the results much. Nevertheless, to avoid the risk that our results are driven by a few individuals, in our subsequent analysis we windsorize the income data at the 1% and 99% levels for both 2008 and 2015.

D. Industry Differences

The information reported to the career services office includes the employers' names, which we use to classify them into three broad industry categories. Specifically, we use two-digit NAICS industry codes to classify each employer into finance (two-digit NAICS code 52), professional services (which we refer to as "consulting," two-digit NAICS code 54), and "other" (the remaining two-digit codes). The general perception is that salaries and career paths in these industries differ, with finance and consulting offering higher pay-for-performance and higher average compensation. In addition, promotions in finance and consulting tend to occur through an up-or-out system. Panel A of Table III confirms that compensation is higher in consulting and finance and that this difference rises over time. Average total income in consulting and finance is 11% to 19% higher than in other industries in 2008 (t-tests, $p < 0.039$) and becomes 36% to 92% higher in 2015 (t-tests, $p < 0.020$). The bonus component of income also tends to be higher in these industries, particularly finance. Panel B of Table III further shows that these tend to be up-or-out industries, with MBAs leaving consulting and finance to other industries while the converse is not true. Specifically, 27% of MBAs who worked in finance in 2008 and 47% of those who worked in consulting move to other industries by 2015, while only 13% of those who start working in other industries move to either consulting or finance.

In summary, Table III shows that our lab experiment replicates the results of Niederle and Vesterlund (2007), namely, that women shy away from competition. Moreover, our sample exhibits a gender gap in income in both 2008 and 2015. The following sections analyze whether these two facts are related.

III. Preferences for Competition and Earnings in the Lab

We start by analyzing earnings in the lab. We use a measure of participants' earnings that does not depend on the matching realized in the experiment. Specifically, we take the distribution of

Table III. Industry Characteristics

Panel A shows the mean total income earned by MBAs in 2008 and 2015, depending on the industry they work in. It also shows the fraction of this income that is due to bonuses. For MBAs who started in a particular industry in 2008, Panel B shows the fraction who work in each industry in 2015. Industries are based on two-digit NAICS codes: finance corresponds to code 52, consulting to code 54, and "other" to the remaining codes.

Panel A. Income and bonus pay

	Finance	Consulting	$Finance or Consulting$	Other
Mean total income in 2008	178.07	166.25	174.24	150.03
Fraction of income in 2008 from bonuses	0.36	0.26	0.33	0.25
Mean total income in 2015	429.96	304.07	401.35	223.76
Fraction of income in 2015 from bonuses	0.43	0.23	0.38	0.20

Panel B. Industry transitions

	Fraction in 2015 who is working in:			
	Finance	Consulting	$Finance or Consulting$	Other
Started in Finance in 2008	0.68	0.05	0.73	0.27
Started in Consulting in 2008	0.22	0.31	0.53	0.47
Started in Other in 2008	0.06	0.06	0.13	0.87

solved sums and simulate one million matches to obtain the expected experimental earnings of each participant if their payment were based on the third period of the addition task (see Section I).

On average, participants who choose to compete earn substantially more than participants who do not. However, as shown in Table II, compared to MBAs who do not compete, those who chose to compete are significantly better at adding numbers, are more overconfident and risk-loving, and are more likely to be males. In other words, the decision to compete subsumes various characteristics. We follow Buser et al. (2014) and isolate the effect of preferences for competition by controlling for other determinants of choosing the tournament in a regression.

In Table IV, we run a series of linear regressions with the log of the participants' experimental earnings as the dependent variable. In column (1), we use only the variable *competitive*, a dummy variable equal to one when a subject chooses to compete. We control for performance in column (2). After we control for *performance*, which is highly statistically significant, the coefficient on *competitive* remains statistically significant, but its magnitude is much smaller. In column (3) we add the gender dummy and two other explanatory variables *overconfidence* and *risk aversion* all measured as described in Section I. As one would expect, overconfidence has a significantly negative effect on earnings. By contrast, neither gender nor risk aversion are significant determinants of

Table IV. Determinants of Experimental Earnings in the Lab

This table presents regressions of the participants' log of expected experimental earnings if the third period of the addition task is used for payment. Linear estimates are reported with standard errors in parentheses. Performance, overconfidence, and risk aversion are standardized to have a mean of zero and a standard deviation of one. ***, **, and * indicate statistical significance at the 0.01, 0.05, and 0.10 level, respectively.

	(1)	(2)	(3)	(4)
Competitive	0.396***	0.125**	0.191***	0.218***
	(0.057)	(0.049)	(0.051)	(0.048)
Performance		0.405***	0.355***	0.323***
		(0.026)	(0.028)	(0.028)
Woman			−0.021	−0.017
			(0.050)	(0.045)
Risk aversion			0.020	0.017
			(0.022)	(0.020)
Overconfidence			−0.091***	0.061***
			(0.026)	(0.017)
Competitive × Overconfidence				−0.351***
				(0.041)
Obs.	409	409	409	409
F-test	47.678	171.844	72.560	83.518
R^2	0.098	0.462	0.477	0.550

experimental earnings. Adding these explanatory variables does not reduce the coefficient on *competitive*, which remains positive and statistically significant. Lastly, in column (4), we evaluate the insight of the original Niederle and Vesterlund (2007) experiment that being competitive benefits some participants but hurts others. Specifically, we test whether preferences for competition are detrimental for overconfident individuals by including the interaction between the measures of preferences for competition and overconfidence. We observe that the coefficient on *overconfidence* becomes positive, while the coefficient of the interaction is strongly negative and significant. Looking at the magnitudes of the coefficients, a 0.62 standard deviation increase in *overconfidence* is sufficient to eliminate any positive effect of preferences for competition. Thus, it is evident that the combination of preferences for competition and overconfidence negatively affects earnings.[16]

[16] In the experiment, the average competition-averse participant underestimates their performance in absolute terms. Underestimating one's performance in absolute but not relative terms is commonly observed in experimental tasks that are considered difficult (see Moore and Healy, 2008). Thus, a bit of overconfidence is good for competition-averse participants because it corrects a systematic bias. For competition-loving participants, in contrast, overconfidence has a clear negative effect.

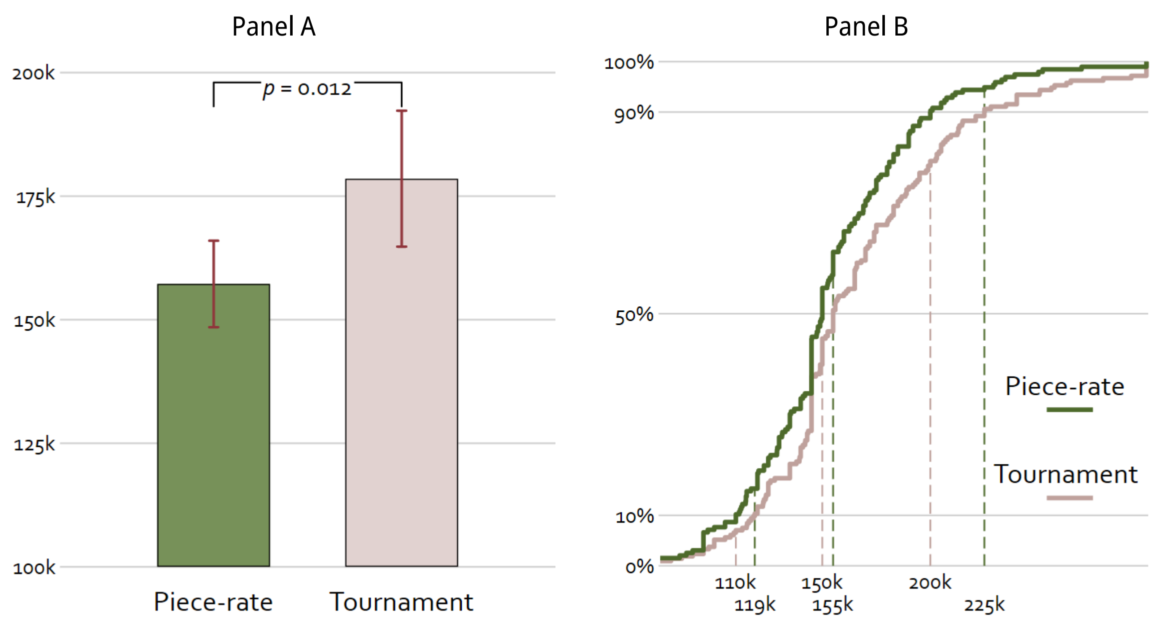

Figure 1. Total income in 2008 depending on tournament choice

Panel A shows the mean total income in 2008 and the corresponding 95% confidence intervals. Panel B shows the cumulative distribution of total income in 2008.

IV. Preferences for Competition and Income in 2008

We now move to our first income data. Figure 1, Panel A shows that students choosing the tournament in a lab experiment at the beginning of their MBA are offered higher earnings two years later in their first job post-MBA. On average, participants who chose the tournament earn $21K more than participants who chose the piece-rate payment scheme (*t*-test, p = 0.012). The difference in earnings is larger for top earners (see Figure 1, Panel B).

Does this difference in earnings persist once we control for other determinants of choosing to compete? To address this question, in Table V we run a series of linear regressions with the log of participants' total income in 2008 as the dependent variable. As above, we control for the gender and competitive dummies, overconfidence, risk aversion, and performance in the adding task.

We find that competition-loving MBAs earn 7.9 log points more at graduation than do their competition-averse counterparts. This effect is substantial (≈$13K) and statistically different from zero at the 5% level. Cortés et al. (2023) present evidence that women's higher levels of risk aversion and men's higher levels of overconfidence help explain the evolution of gender differences in salaries over the job search period. In our case, however, risk aversion and overconfidence are insignificant.

We also find that women make 10.7 log points less in total income, a statistically significant difference (≈$17K less, see column (1)). Given the tendency for wage compression at this stage of an

Table V. Determinants of Income in 2008

This table presents regressions of the log of total income in 2008 in column (1), the log of base salary in 2008 in column (2), a hurdle model of the likelihood of obtaining a bonus in column (3) and its size in column (4), a hurdle model of the likelihood of obtaining a one-off bonus in column (5) and its size in column (6). Hurdle model of the likelihood of obtaining a guaranteed performance bonus in column (7) and its size in column (8). Linear estimates are reported in columns (1), (2), (4), (6), and (8). Marginal effects are reported in columns (3), (5), and (7). *Overconfidence* and *risk aversion* are standardized to have a mean of zero and a standard deviation of one. All regressions also include *performance* as a control. Regressions in Panel A do not include industry fixed effects, while those in Panel B do. Standard errors are in parentheses. ***, **, and * indicate statistical significance at the 0.01, 0.05, and 0.10 level, respectively.

	Total	*Base*	Total bonus		One-off bonus		Perform. bonus	
	income	*salary*	*Obtain*	*Size*	*Obtain*	*Size*	*Obtain*	*Size*
	Panel A. Without industry fixed effects							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Woman	−0.107***	−0.010	0.034	−0.378***	0.039	−0.244***	−0.073	−0.499**
	(0.036)	(0.017)	(0.029)	(0.079)	(0.032)	(0.072)	(0.056)	(0.231)
Competitive	0.079**	0.022	0.013	0.158**	0.021	0.044	0.010	0.571***
	(0.036)	(0.017)	(0.029)	(0.079)	(0.032)	(0.073)	(0.055)	(0.211)
Overconfidence	0.002	0.002	0.014	−0.032	0.008	−0.027	−0.014	0.111
	(0.018)	(0.009)	(0.015)	(0.040)	(0.016)	(0.037)	(0.028)	(0.110)
Risk aversion	0.007	0.013*	−0.013	−0.001	−0.013	−0.056*	−0.016	0.122
	(0.016)	(0.007)	(0.012)	(0.036)	(0.014)	(0.033)	(0.025)	(0.104)
Obs.	409	409	409	380	409	374	409	153
F-test/χ^2 test	3.686	0.975	3.705	31.981	3.916	18.800	3.54	16.286
R^2	0.044	0.012						
	Panel B. With industry fixed effects							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Woman	−0.104***	−0.035**	0.029	−0.300***	0.036	−0.147**	−0.114**	−0.473**
	(0.036)	(0.015)	(0.029)	(0.076)	(0.033)	(0.066)	(0.057)	(0.231)
Competitive	0.062*	0.009	0.012	0.124*	0.017	0.007	0.034	0.478**
	(0.036)	(0.015)	(0.029)	(0.075)	(0.032)	(0.066)	(0.057)	(0.215)
Overconfidence	−0.001	−0.001	0.014	−0.037	0.007	−0.030	−0.013	0.101
	(0.018)	(0.008)	(0.015)	(0.038)	(0.016)	(0.033)	(0.029)	(0.110)
Risk aversion	0.007	0.004	−0.015	0.022	−0.015	−0.029	−0.028	0.126
	(0.016)	(0.007)	(0.013)	(0.034)	(0.014)	(0.029)	(0.025)	(0.103)
Obs.	409	409	409	380	409	374	409	153
F-test/χ^2 test	4.359	17.282	4.992	86.274	5.033	116.100	28.058	19.912
R^2	0.071	0.232						

MBA's career, and given that most companies have predetermined wages for newly hired MBAs, this result is notable. This gender gap is in line with Bertrand et al. (2010), who study the same population from 1990 to 2006 and report a gender gap at graduation of 11.3 log points.

Does accounting for the effect of preferences for competition help explain the gender pay gap? If we run the specification of column (1) but exclude the competition-loving variable, the coefficient on the gender dummy equals 11.7 log points. Hence, controlling for preferences for competition reduces the magnitude of the gender coefficient by 1 log point (8% of the gender gap), a modest but nonnegligible effect.[17]

To better understand the relationship between income and preferences for competition, we separate the base salary and bonuses in columns (2) to (4) .[18] In column (2), the dependent variable is the log of the base salary in 2008. The explanatory variables are the same as in column (1). The results show that there is no gender gap in base salary. Similarly, MBAs who like to compete do not receive larger base pay. Since not all MBAs receive a bonus, and we estimate the regressions in logs, we use a two-step hurdle model to estimate the impact of the independent variables first on the probability of getting a bonus (column (3)) and then on the magnitude of the bonus (column (4)) (Cragg, 1971).

Neither preferences for competition nor gender predict the probability of receiving a bonus, but this is unsurprising since almost everyone (93%) receives some form of bonus. By contrast, both preferences for competition and gender are correlated with the size of the bonuses. In particular, competition-loving MBAs receive \$8K (15.8 log points) more bonus pay, while women receive \$18K (37.8 log points) less. In columns (5) to (8), we further divide the bonuses into one-off and guaranteed performance bonuses. Preferences for competition are strongly associated with the magnitude of the guaranteed performance bonus, with competition-loving MBAs obtaining a bonus that is 57.1 log points higher ($\approx$\$13K) than other MBAs. By contrast, preferences for competition do not appear to affect the amount of the one-off bonus. A possible explanation for the discrepancy between one-off and performance bonuses is that one-off bonuses do not vary much across individuals. This is not what we find, however, one-off bonuses are \$25K at the 25th percentile and

[17]The fraction of the gender gap explained by preferences for competition in our study is consistent with Buser et al. (2020), who find that preferences for competition explain 7.6% of the gender gap among college-educated individuals. Although this fraction might be considered small, we note that the fraction of the gender gap explained by preferences for competition is one of the largest compared to other psychological traits (see Buser et al., 2020).

[18]As previously described, we group the various bonuses into two components: one-off bonuses (relocation, tuition, sign-on, and retention) and guaranteed performance bonuses (stock options, profit sharing, guaranteed performance, and other). In a robustness test, we dropped "other bonuses" from the latter category. The results are unchanged (see Table IAIX in the Internet Appendix).

$55K at the 75th percentile, an interquartile range of $30K, which is similar to that of guaranteed performance bonuses ($37K).

The gender dummy affects the amount but not the presence of both types of bonuses. On average, women get a one-off bonus that is 24.4 log points smaller ($\approx$$9K) and a guaranteed performance bonus that is 49.9 log points smaller ($\approx$$10K). It is notable that we observe these large differences despite pressure at graduation toward gender equality.

Some industries tend to pay MBAs significantly more (Oyer, 2008). Income can therefore vary because of differences in the industry chosen by MBAs at graduation. Since one of the effects of preferences for competition could be different sorting across industries, we initially chose not to control for the industry to estimate the full effect of preferences for competition on income. However, it is interesting to see how the results change if we control for the industry chosen by the MBAs at graduation. We report this analysis in Panel B of Table V. As explained in Section I, we classify employers into three industries: finance, consulting, and the rest. Roughly a third of the MBAs chose each industry. The coefficients on both the preferences for competition and the gender dummies are only slightly smaller. Thus, industry sorting does not seem to be the primary driver of our results.[19]

So far, we have not provided evidence on whether the effect of preferences for competition depends on the level of overconfidence, as suggested by the experimental findings of Niederle and Vesterlund (2007) and our analysis in Section III. We do so in Table VI by adding the interaction of these two variables to the specifications used in Table V. The coefficient on the interaction between overconfidence and competition measures is negative in all but one specification. However, it is not statistically or economically significant in any regression. Moreover, if we compare these results to those in Table V, we see that the inclusion of the interaction term does not have a noticeable impact on the coefficients on the other variables. These results are consistent with income not being closely tied to performance at this point in the MBAs' careers, that is, at graduation.

A. Robustness

The difference in the impact of preferences for competition between base salaries and bonus pay is puzzling. A possible explanation is that MBAs with preferences for competition seek jobs with a larger variable component in their salary as they prefer high rewards. To address this possibility,

[19]We report results of two other robustness checks in the Internet Appendix. In Table IAVI, we evaluate whether we are overestimating the effect of preferences for competition due to potential measurement errors in the control variables (Gillen et al., 2019; van Veldhuizen, 2022). In Table IAVII, we repeat our basic specification after adding a large set of individual controls to the regression (following Bertrand et al., 2010). In both cases, we find very similar results.

Table VI. Interaction between Preferences for Competition and Overconfidence in 2008

This table presents regressions of the log of total income in 2008 in column (1), the log of base salary in 2008 in column (2), a hurdle model of the likelihood of obtaining a bonus in column (3) and its size in column (4), a hurdle model of the likelihood of obtaining a one-off bonus in column (5) and its size in column (6), and a hurdle model of the likelihood of obtaining a guaranteed performance bonus in column (7) and its size in column (8). Linear estimates are reported in columns (1), (2), (4), (6), and (8). Marginal effects are reported in columns (3), (5), and (7). Overconfidence and risk aversion are standardized to have a mean of zero and a standard deviation of one. All regressions also include performance as a control. Regressions in Panel A do not include industry fixed effects, while those in Panel B do. Standard errors are in parentheses. ***, **, and * indicate statistical significance at the 0.01, 0.05, and 0.10 level, respectively.

	Total income	*Base salary*	Total bonus *Obtain*	Total bonus *Size*	One-off bonus *Obtain*	One-off bonus *Size*	Perform. bonus *Obtain*	Perform. bonus *Size*
	Panel A. Without industry fixed effects							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Woman	−0.107***	−0.010	0.034	−0.378***	0.039	−0.244***	−0.074	−0.506**
	(0.036)	(0.017)	(0.029)	(0.079)	(0.033)	(0.072)	(0.056)	(0.232)
Competitive	0.081**	0.022	0.013	0.163**	0.022	0.046	0.016	0.572***
	(0.036)	(0.017)	(0.029)	(0.079)	(0.032)	(0.073)	(0.056)	(0.211)
Overconfidence	0.011	0.005	0.014	−0.002	0.002	−0.017	0.020	0.137
	(0.023)	(0.011)	(0.019)	(0.051)	(0.022)	(0.046)	(0.036)	(0.137)
Competitive ×	−0.020	−0.008	0.002	−0.068	0.013	−0.024	−0.080	−0.064
Overconfidence	(0.032)	(0.015)	(0.026)	(0.070)	(0.029)	(0.064)	(0.051)	(0.203)
Risk aversion	0.007	0.013*	−0.013	−0.002	−0.013	−0.057*	−0.017	0.121
	(0.016)	(0.007)	(0.013)	(0.036)	(0.014)	(0.033)	(0.025)	(0.104)
Obs.	409	409	409	380	409	374	409	153
F-test/χ^2 test	3.130	0.858	3.731	33.003	4.182	18.941	6.108	16.395
R^2	0.045	0.013						
	Panel B. With industry fixed effects							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Woman	−0.104***	−0.035**	0.027	−0.300***	0.033	−0.146**	−0.111**	−0.480**
	(0.036)	(0.015)	(0.026)	(0.076)	(0.029)	(0.066)	(0.055)	(0.232)
Competitive	0.063*	0.009	0.012	0.129*	0.018	0.009	0.040	0.478**
	(0.036)	(0.015)	(0.030)	(0.075)	(0.033)	(0.066)	(0.057)	(0.215)
Overconfidence	0.006	0.001	0.013	−0.009	0.002	−0.025	0.022	0.130
	(0.023)	(0.009)	(0.019)	(0.048)	(0.022)	(0.042)	(0.036)	(0.137)
Competitive ×	−0.017	−0.005	0.002	−0.064	0.013	−0.013	−0.083	−0.072
Overconfidence	(0.031)	(0.013)	(0.026)	(0.066)	(0.028)	(0.058)	(0.052)	(0.201)
Risk aversion	0.007	0.004	−0.015	0.021	−0.015	−0.029	−0.029	0.125
	(0.016)	(0.007)	(0.013)	(0.034)	(0.014)	(0.029)	(0.026)	(0.103)
Obs.	409	409	409	380	409	374	409	153
F-test/χ^2 test	3.845	15.105	5.015	87.425	5.293	116.169	30.694	20.057
R^2	0.071	0.232						

we use a clever feature of the experimental design of Niederle and Vesterlund (2007), namely, participants make two choices between tournament and piece rate. In the third period participants perform under the chosen payment scheme, while in the fourth period the payment scheme is simply applied to their past performance (see footnote 9). Because it does not include performing in a competitive environment, Niederle and Vesterlund (2007) argue that this latter choice between piece rate and tournament is unaffected by the participants' preferences for competition and is instead determined by preferences for nonlinear payoffs that reward high performers. In Table IAVIII in the Internet Appendix, we replicate the analysis in Table V, after adding as an explanatory variable a dummy equal to one if an individual chooses tournament pay in the fourth period. Adding this variable enables us to test whether the effect of the competition variable in Table V is driven by preferences for competition or a "preference for high rewards."

The preference-for-high-rewards variable always has a small coefficient that is statistically indistinguishable from zero. By contrast, the coefficient on *competitive* remains substantially unchanged in all specifications. These results provide compelling evidence that the association between the tournament payment scheme and income is indeed driven by participants' preferences for competition and is not related to the choice of tournament compensation per se.

An alternative explanation is that our measure of preferences for competition instead captures a tendency to boast. Kirby (2017) studies income reported by employees of top consulting firms that tend to offer standardized pay packages to MBAs. He finds that men report earning $8K more than women, with all of the difference concentrated on the bonuses. His interpretation is that MBAs are given a range for the performance bonus, and men report bonuses towards the top of the range, while women do not.[20] This interpretation would imply that our participants disregarded the instructions from the career services office, which explicitly requests that the minimum of a range be reported when offered a range in the bonus. Could this behavior explain our results?

Note that we already include a direct measure of overconfidence in Table V (Panels A and B), namely, the difference between an individual's actual and expected rank. Consistent with Kirby (2017), this variable positively correlates with being male (see Table I). However, overconfidence is not a significant predictor of income or bonuses in 2008. These results suggest that overreporting due to overconfident beliefs is an unlikely explanation for the relationship between preferences for competition and income. We test this explanation further by introducing a direct measure of the tendency to boast.

Two years after the initial experiment, a subset of the MBAs (95) participated in another exper-

[20]Kirby (2017) does not observe the actual bonus amounts paid, and thus, he cannot confirm whether men or women are more accurate in their expectations.

iment. In the first part of that experiment, they were asked, in private, to recall the number of additions they correctly answered two years before. Students were incentivized to give a correct answer.[21] The answers, collected in private, were never communicated to others. Students were then randomly matched into groups of four and asked to communicate to their group members their expected performance if they were to redo the task (see Reuben et al., 2012). The difference between the recalled performance in private and the performance communicated to others can be seen as a proxy for the willingness to boast.[22] In Table IAX in the Internet Appendix, we use this measure to predict income. We find that it correlates negatively with salary (not positively as expected), albeit the effect is not significant. More importantly, its introduction has no impact on the coefficient for preferences for competition. Thus, we do not find much support for either overconfidence or boasting as explanations for the association between preferences for competition and income.

V. Preferences for Competition and Income in 2015

In Table VII, we analyze the relationship between 2015 income and preferences for competition. We begin using the same specification as in Table V. In column (1), we regress the log of total income in 2015 on the gender dummy, our measures of preferences for competition and overconfidence, and our standard set of control variables.

The coefficient on preferences for competition in 2015 is half the size of what it was in 2008 and is no longer statistically different from zero. Unlike the results at graduation, the coefficient on risk aversion is larger and has a significantly negative impact on income. The coefficient on overconfidence is also negative and larger in magnitude, reaching statistical significance at the 10% level.

[21] If a student's estimate was within one addition of their actual performance, they earned $50, otherwise they earned $0.

[22] The purpose of communicating their expected performance is for groups to select a representative who then competes with the representatives from other groups in an incentivized tournament. In other words, individuals' preferences for competition might be one of the motivations to boast. Unlike in Niederle and Vesterlund (2007), boasting does not guarantee participation in the tournament, and one's performance in the tournament affects the earnings of the entire group. In contrast to overconfidence, we do not find that men have a higher tendency to boast (28% of men boast compared to 38% of women). Overall, men do report higher performance than women. However, this difference is because they genuinely believe they are better and not because they strategically inflate their performance. In other words, they are "honestly" overconfident. This lack of a gender difference is also consistent with Healy and Pate (2011), who find no gender difference in competition entry when competing in teams. For more details on this result, see Reuben et al. (2012).

Table VII. Determinants of Income in 2015

This table presents regressions of the log of total income in 2015 in column (1), the log of base salary in 2015 in column (2), and a hurdle model of the likelihood of obtaining a bonus in column (3) and its size (in logs) in column (4). Linear estimates are reported in columns (1), (2), and (4). Marginal effects are reported in column (3). Overconfidence and risk aversion are standardized to have a mean of zero and a standard deviation of one. Regressions that include overconfidence also include performance as a control. Regressions in Panel A do not include industry fixed effects, while those in Panel B do. Standard errors are in parentheses. ***, **, and * indicate statistical significance at the 0.01, 0.05, and 0.10 level, respectively.

	Total income	*Base salary*	Perform. bonus *Obtain*	Perform. bonus *Size*
	Panel A. Without industry fixed effects			
	(1)	(2)	(3)	(4)
Woman	−0.384***	−0.194**	−0.002	−0.986***
	(0.109)	(0.083)	(0.050)	(0.247)
Competitive	0.035	0.003	0.003	0.085
	(0.091)	(0.060)	(0.045)	(0.173)
Overconfidence	−0.080*	−0.051*	−0.064**	−0.017
	(0.048)	(0.029)	(0.026)	(0.101)
Risk aversion	−0.103**	−0.053*	−0.023	−0.113
	(0.044)	(0.032)	(0.020)	(0.087)
Obs.	250	250	250	218
F-test/χ^2 test	5.755	2.595	9.02	27.801
R^2	0.096	0.057		
	Panel B. With industry fixed effects			
	(1)	(2)	(3)	(4)
Woman	−0.218**	−0.142*	0.026	−0.623***
	(0.107)	(0.084)	(0.048)	(0.235)
Competitive	0.001	−0.008	−0.007	0.030
	(0.082)	(0.059)	(0.043)	(0.157)
Overconfidence	−0.083**	−0.055*	−0.062**	−0.052
	(0.042)	(0.028)	(0.024)	(0.093)
Risk aversion	−0.122***	−0.058*	−0.028	−0.154*
	(0.041)	(0.031)	(0.019)	(0.082)
Obs.	250	250	250	218
F-test/χ^2 test	14.152	4.678	17.65	127.869
R^2	0.269	0.129		

In line with previous research (Bertrand et al., 2010), the gender gap is much larger several years after graduation. The coefficient oo the gender dummy more than tripled from 10.7 log points in 2008 to 38.4 log points in 2015, implying an increase in the gender gap from $17K to $89K.

In column (2), we reestimate the same specification with the log of the base salary as a dependent variable. As at graduation, preferences for competition exhibit a statistically and economically insignificant effect on base salary. Unlike the results at graduation, the gender dummy is significant even for the base salary. Women earn 19.4 log points less in base salary.

In the following two columns, we run a two-step hurdle model to estimate, in the first stage, the probability of getting a bonus (column (3)) and, in the second stage, the log of the bonus received (column (4)). Overall, 87% of the sample received a bonus, which was $151K on average. In 2015, preferences for competition do not predict the probability of receiving a bonus or its magnitude seven years later. As at graduation, there is no gender difference in the likelihood of receiving a bonus, but conditional on getting one, men receive much larger bonuses than women. A notable difference between the results at graduation and in 2015 is that the coefficient on the overconfidence measure becomes negative and significant. As in the experiment (Table IV), when MBAs are paid based on performance, being overconfident, other things being equal, is correlated with lower pay.

The inclusion of industry fixed effects in Panel B of Table VII noticeably reduces the coefficients on the gender dummy, but it does not affect the coefficients on preferences for competition, overconfidence, and risk aversion.

In Table VIII, we explore the effect of including the interaction between overconfidence and preferences for competition in the regressions reported in Table VII. The estimates in column (1) show that total income in 2015 is positively associated with preferences for competition but only when the latter is not accompanied by overconfidence. The interaction is negative, large, and statistically significant.

Figure 2 depicts the effect of this interaction when we do not use industry controls (i.e., Panel A). The figure shows the impact of preferences for competition on income at varying degrees of overconfidence (blue lines), along with the corresponding 90% confidence intervals (red lines). The vertical blue dotted line corresponds to the average overconfidence of men, the vertical red dotted line to the average overconfidence of women, and the vertical black dotted line to zero overconfidence (i.e., the point where a participant's expected ranking equals their actual ranking). As can be seen, the effect of preferences for competition is economically meaningful. A competition-loving MBA whose overconfidence is one standard deviation below the mean earns $74K more than the average MBA, while a competition-loving MBA whose overconfidence is one standard deviation above the mean earns $38K less. Since the average income is around $255K, these are economically significant swings. Consistent with the argument above, columns (2) to (4) show that the interaction between overconfidence and preferences for competition is stronger for the income

Table VIII. Interaction between Preferences for Competition and Overconfidence in 2015

This table presents regressions of the log of total income in 2015 in column (1), the log of base salary in 2015 in column (2), and a hurdle model of the likelihood of obtaining a bonus in column (3) and its size (in logs) in column (4). Linear estimates are reported in columns (1), (2), and (4). Marginal effects are reported in column (3). Overconfidence and risk aversion are standardized to have a mean of zero and a standard deviation of one. Regressions that include overconfidence also include performance as a control. Regressions in Panel A do not include industry fixed effects, while those in Panel B do. Standard errors are in parentheses. ***, **, and * indicate statistical significance at the 0.01, 0.05, and 0.10 levels, respectively.

	Total income	*Base salary*	Perform. bonus *Obtain*	Perform. bonus *Size*
	Panel A. Without industry fixed effects			
	(1)	(2)	(3)	(4)
Woman	−0.391***	−0.197**	−0.004	−1.008***
	(0.106)	(0.083)	(0.048)	(0.240)
Competitive	0.055	0.012	0.025	0.089
	(0.089)	(0.060)	(0.047)	(0.170)
Overconfidence	0.011	−0.012	−0.040	0.154
	(0.051)	(0.030)	(0.035)	(0.105)
Competitive × Overconfidence	−0.219***	−0.095*	−0.050	−0.425***
	(0.077)	(0.052)	(0.041)	(0.162)
Risk aversion	−0.099**	−0.052	−0.020	−0.109
	(0.043)	(0.032)	(0.019)	(0.086)
Obs.	250	250	250	218
F-test/χ^2 test	5.917	2.368	13.175	33.804
R^2	0.120	0.067		
	Panel B. With industry fixed effects			
	(1)	(2)	(3)	(4)
Woman	−0.226**	−0.146*	0.022	−0.645***
	(0.106)	(0.084)	(0.042)	(0.233)
Competitive	0.017	−0.002	0.013	0.035
	(0.080)	(0.059)	(0.045)	(0.153)
Overconfidence	−0.017	−0.027	−0.040	0.073
	(0.050)	(0.030)	(0.032)	(0.108)
Competitive × Overconfidence	−0.159**	−0.068	−0.046	−0.310**
	(0.070)	(0.050)	(0.039)	(0.149)
Risk aversion	−0.118***	−0.057*	−0.025	−0.150*
	(0.041)	(0.031)	(0.018)	(0.081)
Obs.	250	250	250	218
F-test/χ^2 test	14.190	4.190	20.858	134.867
R^2	0.281	0.134		

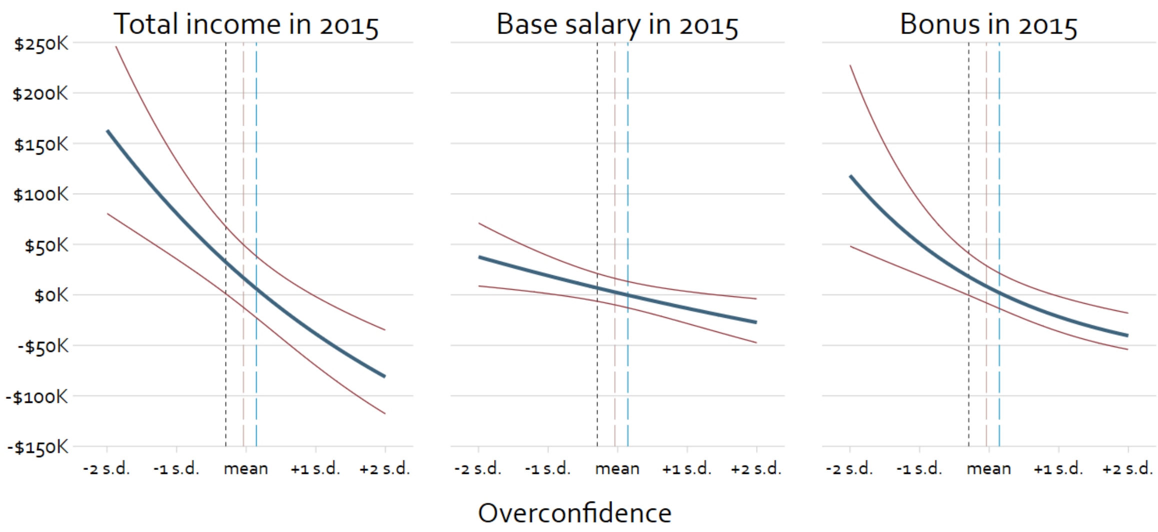

Figure 2. Estimated marginal effect of preferences for competition on income in 2015 at different levels of overconfidence

The figure is based on the regressions in Panel A of Table VIII. Blue lines correspond to the estimated marginal effect and red lines to 90% confidence intervals. The blue dashed line corresponds to the average overconfidence of men, the red dashed line to the average overconfidence of women, and the black dotted line to zero overconfidence (i.e., the point where a participant's expected ranking equals their actual ranking).

component most firmly tied to individual performance, namely, the bonus (see also Figure 2).[23]

A. Robustness

Why do preferences for competition and overconfidence have different effects in 2008 and 2015? We first check whether the differences are due to the reduced sample size (only 61% of the sample answered the 2015 follow-up survey). To do so, in Table IX we reestimate the regressions for income in 2008 solely for the sample of MBAs for whom we have 2015 data. We concentrate on regressions of total income and the magnitude of the bonuses since these are the specifications for which preferences for competition have an effect in 2008.

In columns (1) and (2) of Table IX, the coefficients on the preferences for competition measure are about the same magnitude as in the full sample but are not statistically different from zero. Thus, in the 2015 sample we have a power issue. Still, this is not the only reason the coefficient

[23]The Internet Appendix presents a series of robustness checks. Specifically, we show that the results in Tables VII and VIII are robust to potential measurement errors in the control variables (Table IAXII), adding a large set of individual controls (Table IAXIII), and considering participants' "preference for high rewards" (Table IAXIV). In Table IAXV, we run the same regressions as in Table VIII, including the interaction between preferences for competition and the other determinants of tournament entry in the experiment, risk aversion and performance in the adding task. These other interactions with preferences for competition are not statistically significant and do not substantially affect the interaction with overconfidence.

Table IX. Determinants of Income in 2008 using the 2015 Sample

This table presents regressions of the log of total income in 2008 in columns (1) and (2), and hurdle models of the size of the total bonus in columns (3) and (4), the size of the one-off bonus in columns (5) and (6), and the magnitude of the guaranteed performance bonus in columns (7) and (8). The regressions of the likelihood of receiving the various bonuses are omitted. Overconfidence and risk aversion are standardized to have a mean of zero and a standard deviation of one. All regressions also include performance as a control. Regressions in Panel A do not include industry fixed effects, while those in Panel B do. Standard errors are in parentheses. ***, **, and * indicate statistical significance at the 0.01, 0.05, and 0.10 level, respectively.

	Total	*Base*	Total bonus		One-off bonus		Perform. bonus	
	income	*salary*	*Obtain*	*Size*	*Obtain*	*Size*	*Obtain*	*Size*
	Panel A. Without industry fixed effects							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Woman	−0.126***	−0.126***	−0.367***	−0.370***	−0.235***	−0.236***	−0.744**	−0.791**
	(0.042)	(0.042)	(0.094)	(0.094)	(0.090)	(0.091)	(0.311)	(0.316)
Competitive	0.062	0.063	0.151	0.159*	0.097	0.100	0.458*	0.465*
	(0.049)	(0.048)	(0.097)	(0.095)	(0.086)	(0.085)	(0.272)	(0.271)
Overconfidence	0.024	0.026	−0.032	−0.002	−0.046	−0.036	0.188	0.270
	(0.022)	(0.028)	(0.054)	(0.064)	(0.050)	(0.060)	(0.142)	(0.176)
Competitive ×		−0.004		−0.071		−0.025		−0.209
Overconfidence		(0.039)		(0.091)		(0.089)		(0.267)
Risk aversion	−0.015	−0.014	−0.020	−0.019	−0.051	−0.051	0.062	0.068
	(0.022)	(0.022)	(0.043)	(0.043)	(0.037)	(0.037)	(0.135)	(0.135)
Obs.	250	250	237	237	232	232	101	101
F-test/χ^2 test	3.523	2.930	20.382	21.810	14.845	15.343	12.317	13.005
R^2	0.057	0.057						
	Panel B. With industry fixed effects							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Woman	−0.122***	−0.122***	−0.297***	−0.298***	−0.138	−0.138	−0.750**	−0.791**
	(0.041)	(0.041)	(0.091)	(0.091)	(0.084)	(0.084)	(0.331)	(0.343)
Competitive	0.054	0.054	0.113	0.119	0.041	0.041	0.448*	0.452*
	(0.049)	(0.049)	(0.094)	(0.091)	(0.076)	(0.073)	(0.265)	(0.260)
Overconfidence	0.018	0.016	−0.042	−0.019	−0.052	−0.053	0.158	0.239
	(0.021)	(0.028)	(0.049)	(0.061)	(0.042)	(0.052)	(0.122)	(0.162)
Competitive ×		0.005		−0.053		0.002		−0.202
Overconfidence		(0.038)		(0.082)		(0.073)		(0.218)
Risk aversion	−0.011	−0.011	0.011	0.011	−0.016	−0.016	0.061	0.068
	(0.021)	(0.022)	(0.041)	(0.041)	(0.032)	(0.032)	(0.140)	(0.139)
Obs.	250	250	237	237	232	232	101	101
F-test/χ^2 test	3.607	3.137	53.670	54.389	87.840	87.819	18.342	18.984
R^2	0.079	0.079						

on preferences for competition is not statistically significant with 2015 income. The effect of preferences for competition on income in 2008 was driven by its effect on the bonus, particularly the guaranteed performance bonus. Columns (3), (4), (7), and (8) show that these coefficients are roughly the same when restricting the 2008 regressions to the 2015 sample and are much larger than the coefficients obtained with the 2015 income data. For example, in column (7) of Panel B, competition-loving MBAs receive a bonus in 2008 that is 44.8 log points higher (significant at the 10% level), but they receive a bonus in 2015 that is only 3.0 log points higher (not significant, see column (4) of Panel B in Table VII).

One might worry that these results are driven by the selection of respondents into the 2015 survey. The 2015 respondents tend to be less overconfident, have higher salaries at graduation, and are disproportionately male, all characteristics that correlate positively with income seven years later. The fact that the 2015 survey has fewer overconfident MBAs than the original sample could reduce the statistical power of the regressions. However, this issue does not seem to be a problem as our results are statistically significant. To address the potential biases that could arise from selection, in the Internet Appendix we use a Heckman selection model to evaluate the robustness of our results.[24] The results remain unchanged. Similarly, the regressions in Table IX demonstrate that the change over time in the interaction between preferences for competition and overconfidence, which has a small coefficient in 2008 and a large and significant one in 2015, is not driven by selection in the 2015 sample. In all regressions in Table IX, the coefficient on the interaction is much smaller in 2008 than in 2015 and is never statistically significant.

In 2015, there is much more variability in the income data, mainly because industry differences matter much more after seven years. However, the fact that the coefficient on preferences for competition remains insignificant in all specifications while the coefficients on overconfidence and risk aversion are significantly negative in three of the four specifications suggests that the lack of significance of preferences for competition is not due to an increase in the variability of income or to an overall decline in the explanatory power of measures elicited nine years before. Moreover, the fact that the interaction between preferences for competition and overconfidence is statistically significant seven years after graduation (and nine years after these traits were measured) reassures us that our measure of preferences for competition is not a noisy measure.[25]

[24]More specifically, we use independent measures of the MBAs' tendency to answer university surveys to fit a Heckman selection model and account for the impact of the probability of answering the 2015 survey on the estimates of Tables VII and VIII. See Table IAXI and the corresponding description in the Internet Appendix for more details.

[25]In Tables VII and VIII, the inclusion of industry fixed effects has a more noticeable effect on the other coefficients than in Tables V and VI. For instance, the joint explanatory power increases substantially in all specifications, and the coefficient on the gender dummy drops by a third in absolute value (but remains negative and statistically significant).

The main difference between the 2008 and 2015 income data is that in 2015 income is highly dependent on past performance, while in 2008 it is not. Imagine that in the lab experiment, all participants who choose to compete are guaranteed the expected earnings of the average participant who competes, and all participants who choose not to compete are paid the expected earnings of participants who choose not to compete. By construction, we would observe that earnings positively correlate with the decision to compete but not with its interaction with overconfidence. This result is consistent with the relationship between income and preferences for competition in 2008. At graduation, MBAs are guaranteed a bonus and given a salary based on expectations. By contrast, in 2015 income is based on realized performance over the course of the employee's career. In this case, there should be a negative correlation between income and the interaction between preferences for competition and overconfidence, as observed in the lab experiment (see Table IV). Our results are consistent with this view.

VI. Exploring the Mechanism

To further investigate why preferences for competition and overconfidence impact income, we look at additional evidence from the MBAs' career trajectories. Ideally, we would test whether competition-loving and overconfident individuals are more likely to be fired or asked to leave because of their poor performance. We do not have such information. However, we know whether individuals changed jobs and whether doing so implied leaving a high-paying, high-reward industry. We also know whether they interrupted their career for more than six months, whether they were promoted, and the number of hours worked in 2015.

We begin by analyzing the probability of working in a high-reward industry. High-reward industries (consulting and finance) tend to have higher incomes, higher pay for performance, and up-or-out career trajectories. For instance, while 34% of the MBAs who started working in consulting or finance in 2008 left for another industry by 2015, only 6% of those working in consulting or finance in 2015 came from another industry (see Table III).

Table X presents probit regressions of working in a high-reward industry. In columns (1) and (2), the dependent variable equals one if an MBA works in a high-reward industry in 2008. In columns (3) and (4), the dependent variable equals one if an MBA works in a high-reward industry in 2015. In all cases, we report marginal effects.

In 2008, competition-loving MBAs are 13.5 percentage points more likely to work in a high-reward industry, but in 2015 this coefficient is two-thirds smaller and no longer statistically significant. There is no interaction between preferences for competition and overconfidence in 2008, but in

Table X. Determinants of Working in a High-Reward Industry

This table presents regressions of working in either finance or consulting. Marginal effects from probit regressions are reported. Overconfidence and risk aversion are standardized to have a mean of zero and a standard deviation of one. All regressions also include performance as a control. Standard errors are in parentheses. ***, **, and * indicate statistical significance at the 0.01, 0.05, and 0.10 level, respectively.

	High-reward industry in 2008		High-reward industry in 2015	
	(1)	(2)	(3)	(4)
Woman	−0.037	−0.037	−0.186**	−0.194**
	(0.048)	(0.048)	(0.076)	(0.076)
Competitive	0.135***	0.135***	0.043	0.056
	(0.049)	(0.049)	(0.075)	(0.076)
Overconfidence	0.023	0.030	0.018	0.070
	(0.025)	(0.035)	(0.039)	(0.049)
Competitive × Overconfidence		−0.016		−0.121*
		(0.043)		(0.066)
Risk aversion	−0.008	−0.008	0.017	0.020
	(0.021)	(0.021)	(0.032)	(0.032)
Obs.	409	409	250	250
χ^2 test	14.080	14.274	7.872	11.755

2015 a strong interaction emerges. For instance, while being competition-loving increases MBAs' probability of working in a high-reward industry by 17.6 percentage points if their overconfidence is one standard deviation below the mean, being competition-loving decreases this probability by 6.5 percentage points if their overconfidence is one standard deviation above the mean. In other words, overconfident MBAs who are competition-loving tend to choose high-reward industries at graduation but then fail to remain employed in those industries.

In Table XI, we continue this analysis by studying income growth over the seven-year period. The dependent variable in these regressions is log income in 2015 minus log income in 2008. On average, the MBAs' income grows by 44.8 log points, or around $92k. Income growth is not significantly associated with preferences for competition. By contrast, income growth is negatively associated with overconfidence and risk aversion. If overconfidence increases by one standard deviation, income growth declines by 10.5 log points (≈$25K). For risk aversion, the equivalent decline is 8.9 log points (≈$22K). The inclusion of industry fixed effects does not affect the results.

Columns (2) and (4) add the interaction between overconfidence and preferences for competition as an independent variable. The effect is negative and statistically significant. While the average income increase for the MBAs is 44.8 log points (≈$92K), competition-loving MBAs whose overconfidence is one standard deviation below the mean see their income increase by 69.5 log points

Table XI. Determinants of Income Growth between 2008 and 2015

This table presents regressions of income growth, the log of total income in 2015 minus the log of total income in 2008. Linear estimates are reported. Overconfidence and risk aversion are standardized to have a mean of zero and a standard deviation of one. All regressions also include performance as a control. Standard errors are in parentheses. ***, **, and * indicate statistical significance at the 0.01, 0.05, and 0.10 level, respectively.

	Without industry fixed effects		With industry fixed effects	
	(1)	(2)	(3)	(4)
Woman	−0.258**	−0.265**	−0.109	−0.117
	(0.109)	(0.107)	(0.109)	(0.109)
Competitive	−0.027	−0.007	−0.057	−0.041
	(0.101)	(0.099)	(0.098)	(0.096)
Overconfidence	−0.105**	−0.015	−0.106**	−0.036
	(0.048)	(0.055)	(0.045)	(0.054)
Competitive × Overconfidence		−0.216***		−0.167**
		(0.080)		(0.075)
Risk aversion	−0.089*	−0.085*	−0.106**	−0.102**
	(0.046)	(0.045)	(0.045)	(0.044)
Obs.	250	250	250	250
F-test	3.835	4.281	8.200	7.914
R^2	0.057	0.077	0.168	0.180

(≈\$164K), while competition-loving MBAs whose overconfidence is one standard deviation above the mean experience an income increase of only 23.4 log points (≈\$43K).

Table XII studies other dimensions of career paths, specifically, the number of different jobs (columns (1) and (2)) and promotions (columns (3) and (4)) since graduation, the average number of hours worked per week, and whether individuals interrupted their careers for six months or more. These measures, collected seven years after graduation, are imperfect proxies for career success.[26] Nonetheless, we explore whether they are related to traits measured prior to graduation and, specifically, whether we can shed light on the mechanism that links income with the interaction between preferences for competition and overconfidence. On average, MBAs had 2.2 jobs since graduating and reported being promoted 2.4 times. However, we do not find that preferences for competition, overconfidence, or gender are significant predictors of the number of jobs

[26] For example, changing jobs could be a measure of success or could be the result of being fired. Even promotions depend on how vertical the organization is and how distant from the top jobs (e.g., CEO) these graduates were when they started at the firm, as well as how many jobs they changed since graduation. Career interruption is a better proxy, but many workers voluntarily decide to interrupt their careers, especially if they want to take care of children or elderly family members. Similar objections could be made with respect to the number of hours worked.

Table XII. Correlates of Income in 2015 and Preferences for Competition and Overconfidence

This table presents regressions of the number of jobs between 2008 and 2015 in columns (1) and (2), the number of promotions between 2008 and 2015 in columns (3) and (4), hours worked per week in columns (5) and (6), and whether the MBA interrupted their career for at least six months in columns (7) and (8). Linear estimates are reported in columns (1) through (6). Marginal effects are reported in columns (7) and (8). Number of jobs, number of promotions, hours worked per week, overconfidence, and risk aversion are standardized to have a mean of zero and a standard deviation of one. All regressions also include performance as a control. Regressions in Panel A do not include industry fixed effects, while those in Panel B do. Standard errors are in parentheses. ***, **, and * indicate statistical significance at the 0.01, 0.05, and 0.10 level, respectively.

	Number of jobs		Number of promotions		Hours worked per week		Career interruption	
	Panel A. Without industry fixed effects							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Woman	0.160	0.162	0.099	0.096	−0.565***	−0.566***	0.082	0.085
	(0.143)	(0.142)	(0.170)	(0.171)	(0.172)	(0.172)	(0.063)	(0.062)
Competitive	0.113	0.107	−0.038	−0.030	−0.057	−0.053	0.017	0.000
	(0.152)	(0.155)	(0.148)	(0.147)	(0.131)	(0.132)	(0.048)	(0.048)
Overconfidence	0.058	0.035	−0.028	0.011	−0.148**	−0.128	0.053**	0.012
	(0.073)	(0.083)	(0.079)	(0.104)	(0.068)	(0.088)	(0.024)	(0.028)
Competitive ×		0.056		−0.094		−0.047		0.086**
Overconfidence		(0.130)		(0.135)		(0.126)		(0.039)
Risk aversion	0.065	0.064	0.019	0.021	0.010	0.011	0.010	0.007
	(0.066)	(0.066)	(0.069)	(0.069)	(0.076)	(0.076)	(0.024)	(0.023)
Obs.	250	250	250	250	250	250	250	250
F-test/χ^2 test	0.951	0.811	0.195	0.288	2.979	2.572	6.149	10.389
R^2	0.016	0.017	0.005	0.007	0.070	0.070		
	Panel B. With industry fixed effects							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Woman	0.078	0.079	−0.011	−0.018	−0.553***	−0.555***	0.070	0.074
	(0.150)	(0.149)	(0.171)	(0.172)	(0.173)	(0.173)	(0.065)	(0.064)
Competitive	0.131	0.131	−0.017	−0.004	−0.061	−0.057	0.021	0.005
	(0.150)	(0.153)	(0.146)	(0.145)	(0.133)	(0.133)	(0.048)	(0.048)
Overconfidence	0.066	0.063	−0.029	0.025	−0.150**	−0.136	0.053**	0.015
	(0.073)	(0.080)	(0.080)	(0.106)	(0.067)	(0.087)	(0.024)	(0.028)
Competitive ×		0.006		−0.129		−0.036		0.082**
Overconfidence		(0.133)		(0.135)		(0.125)		(0.039)
Risk aversion	0.073	0.072	0.032	0.035	0.009	0.010	0.010	0.007
	(0.065)	(0.065)	(0.071)	(0.070)	(0.075)	(0.076)	(0.024)	(0.022)
Obs.	250	250	250	250	250	250	250	250
F-test/χ^2 test	2.537	2.210	1.277	1.277	2.255	2.010	8.705	12.813
R^2	0.062	0.062	0.034	0.038	0.073	0.073		

Table XIII. Career Paths and the Effect of Preferences for Competition and Overconfidence on Income in 2015 (without industry Fixed Effects)

This table presents regressions of the log of total income in 2015 in all columns. Linear estimates are reported. Number of jobs, number of promotions, hours worked per week, overconfidence, and risk aversion are standardized to have a mean of zero and a standard deviation of one. All regressions also include performance as a control. Standard errors are in parentheses. ***, **, and * indicate statistical significance at the 0.01, 0.05, and 0.10 level, respectively.

	(1)	(2)	(3)	(4)	(5)
Woman	−0.370***	−0.401***	−0.267***	−0.338***	−0.214**
	(0.106)	(0.105)	(0.093)	(0.093)	(0.085)
Competitive	0.070	0.058	0.067	0.064	0.086
	(0.088)	(0.087)	(0.086)	(0.088)	(0.081)
Overconfidence	0.015	0.010	0.039	0.019	0.048
	(0.050)	(0.049)	(0.046)	(0.051)	(0.043)
Competitive ×Overconfidence	−0.212***	−0.210***	−0.209***	−0.165**	−0.150**
	(0.077)	(0.075)	(0.071)	(0.073)	(0.067)
Risk aversion	−0.091**	−0.101**	−0.101**	−0.096**	−0.094***
	(0.042)	(0.042)	(0.040)	(0.039)	(0.036)
Number of jobs	−0.131***				−0.091**
	(0.041)				(0.037)
Number of promotions		0.101***			0.056
		(0.037)			(0.037)
Hours worked per week			0.220***		0.214***
			(0.049)		(0.045)
Career interruption				−0.596***	−0.533***
				(0.158)	(0.150)
Obs.	250	250	250	250	250
F-test	7.087	5.886	8.108	6.697	10.168
R^2	0.155	0.141	0.214	0.212	0.330

and promotions they had in the seven years after graduation. By contrast, we find that overconfident MBAs tend to work significantly fewer hours per week and are significantly more likely to have interrupted their careers. When we interact overconfidence with preferences for competition, we find that the interaction does not predict hours worked but is a strong predictor of career interruptions. The predicted probability of facing a career interruption is 15.2% on average; the probability of a career interruption for a competition-loving MBA whose overconfidence is one standard deviation below the mean is much lower (6.3%), while the probability of career interruption is much higher (26.2%) for a competition-loving MBA whose overconfidence is one standard deviation above the mean.

In Tables XIII and XIV, we observe the extent to which these proxies for career paths help explain the effect of the interaction between preferences for competition and overconfidence. We rerun

Table XIV. Career Paths and the Effect of Preferences for Competition and Overconfidence on Income in 2015 (with Industry Fixed Effects)

This table presents regressions of the log of total income in 2015 in all columns. Linear estimates are reported. Number of jobs, number of promotions, hours worked per week, overconfidence, and risk aversion are standardized to have a mean of zero and a standard deviation of one. All regressions also include performance as a control. Standard errors are in parentheses. All regressions include industry fixed effects. ***, **, and * indicate statistical significance at the 0.01, 0.05, and 0.10 level, respectively.

	(1)	(2)	(3)	(4)	(5)
Woman	−0.220**	−0.223**	−0.111	−0.182*	−0.074
	(0.107)	(0.104)	(0.091)	(0.096)	(0.085)
Competitive	0.027	0.018	0.029	0.026	0.043
	(0.080)	(0.076)	(0.078)	(0.078)	(0.069)
Overconfidence	−0.012	−0.021	0.011	−0.008	0.017
	(0.050)	(0.046)	(0.045)	(0.050)	(0.041)
Competitive × Overconfidence	−0.159**	−0.139**	−0.152**	−0.113*	−0.095
	(0.070)	(0.066)	(0.064)	(0.066)	(0.058)
Risk aversion	−0.113***	−0.124***	−0.120***	−0.115***	−0.117***
	(0.040)	(0.039)	(0.038)	(0.037)	(0.035)
Number of jobs	−0.079*				−0.043
	(0.040)				(0.037)
Number of promotions		0.154***			0.105***
		(0.038)			(0.036)
Hours worked per week			0.207***		0.191***
			(0.048)		(0.046)
Career interruption				−0.546***	−0.510***
				(0.153)	(0.143)
Obs.	250	250	250	250	250
F-test	13.078	14.191	19.976	15.031	18.248
R^2	0.293	0.329	0.365	0.358	0.470

the regression of total income reported in Table VIII, including, first separately and then jointly, the number of jobs and promotions, hours worked, and having a career interruption as explanatory variables. Table XIII does not contain industry fixed effects, while Table XIV does.

As one would expect, having a higher number of different jobs and experiencing career interruptions are negatively associated with total income, while the number of promotions and hours worked show a positive association.

Although all of the measures of career paths correlate significantly with income, including them in the regression impacts the coefficients on the interaction between preferences for competition and overconfidence differently. Controlling for the number of jobs, promotions, and hours worked has negligible effects on the coefficient on the interaction effect. However, controlling for career interruptions reduces the size of the interaction's coefficient by around 5 log points, and accounting for industry sorting reduces it by an additional 6 log points. Overall, the coefficient on the interaction between preferences for competition and overconfidence decreases from 21.9 log points in column (1) of Table VIII to 11.7 in column (5) of Table XIV. These results suggest that half of the effect of this interaction on income can be explained by overconfident MBAs with preferences for competition leaving high-reward industries and having more career interruptions. Importantly, these results are consistent with the lab experiments in Table IV. Overconfident students with strong preferences for competition underperformed in the experiment. The same students are more likely to leave high-reward industries and have more career interruptions. These career patterns affect their income seven years after graduation.

VII. Conclusion

We find that preferences for competition have a long-term effect on the income of highly paid business professionals whose compensation depends strongly on their performance. However, most, if not all, of this effect is mediated by overconfidence. In the long term, preferences for competition lead to higher compensation only for individuals who are not overconfident. In contrast, for overconfident individuals, preferences for competition result in lower earnings.

Our paper contributes to the growing literature linking measurable characteristics in the lab with relevant labor-market outcomes to explain some persistent and not fully explained features of the labor market. Our study is distinct as it focuses on high-income earners with high pay-for-performance sensitivity over a seven-year timespan.

Since women shy away from competition, the literature on preferences for competition emerged in the context of understanding gender differences in the labor market. However, while we confirm that men are more competition-loving than women, we find that the gender difference in preferences for competition does not explain the large gender gap in pay among our sample of high-earning business professionals, especially when the pay is based on realized performance. In line with the results of the original lab experiment, our field results suggest that the tendency of women to shy away from competition is offset by the tendency of overconfident men to compete too much.[27]

These findings suggest caution with policies that aim to eliminate gender pay gaps by teaching

[27] As found by Bertrand et al. (2010), the gender gap in our sample is explained to a large extent by differential sorting into high-reward industries and the number of hours worked. Controlling for these two variables reduces the gender pay gap from 39.1 log points in column (1) of Table VIII to only 11.1 log points (not statistically different from zero) in column (3) of Table XIV.

women to compete more. If competition is spurred by higher overconfidence, the effect on the earnings gap might end up being harmful. On the other hand, from an employer's or a social planner's perspective, teaching men to be less overconfident could be more fruitful.

Our analysis is conducted on a sample of high-earning professionals whose income is sensitive to performance. The difference between our results and those based on professions with lower pay-for-performance sensitivity suggests that a key mediator of our effects is performance on the job. Future research can shed more light by directly measuring job performance and explaining how it relates to preferences for competition and overconfidence.

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Internet Appendix for
"Overconfidence and Preferences for Competition"

Section IAI presents a detailed analysis of whether MBAs who consented to the study in 2006 vary systematically from MBAs who did not. Section II presents a similar analysis of whether MBAs who answered the survey in 2015 vary systematically from those who did not. Section IAIII describes in detail the numerous robustness checks reported in the paper but not fully described there due to space constraints. Section IV describes the procedures used to conduct the experiment and survey, including a sample of the instructions used to elicit preferences for competition. Lastly, Section IAV describes the additional variables used in the robustness checks.

IAI. Selection into the Sample in 2006

In this section, we evaluate whether the 409 participants who consented to the analysis of all their data (including their earnings) differ from the 129 participants who consented to the analysis of only some of their data. In the top part of Table IAI, we present the means and standard deviations of variables related to preferences for competition plus the fraction of women. For each variable, the table also displays the *p*-value obtained when we test whether the two groups of participants are significantly different from each other. Specifically, we use simple *t*-tests for the continuous variables and χ^2 tests for categorical variables. In the bottom part of Table IAI, we present the same information for the control variables that we use for the robustness checks in Section IAIII below. We describe these variables and how we collected them in Section IAV below.

By and large, we find no significant differences between the participants who fully consented to the study and those who did not. If we use an unadjusted significance threshold of 5%, we find a significant difference in 4 out of 25 variables (age, GMAT verbal percentile, GPA, and the survey measure of overconfidence). However, if we adjust *p*-values with the Benjamini-Hochberg method to account for multiple comparisons (Benjamini and Hochberg, 1995), we find a significant difference in only one variable (GPA). Importantly for this paper, neither the fraction of women nor the fraction of participants who chose the tournament are significantly different. Moreover, if we test for each gender whether the fraction of individuals who chose the tournament differs between those who fully consented and those who did not, we do not find a statistically significant difference for men ($p = 0.794$) or women ($p = 0.704$).

Finally, to test whether preferences for competition differ between participants who fully consented to the study and those who did not, we run a probit regression with the participants' tour-

Table IAI. Summary statistics depending on consenting to all parts of the study in 2006

This table reports means, standard deviations, and number of observations for variables of interest. The rightmost column displays p-values from tests of equality of distributions between people who consented to the analysis of all their data and those who did not (t-tests for ordinal variables and χ^2 tests for categorical variables).

	Consented			Did not consent			
	mean	*s.d.*	*N*	*mean*	*s.d.*	*N*	$p-value$
Competitive	0.52	0.50	409	0.51	0.50	123	0.867
Performance	2.48	0.77	409	2.52	0.77	123	0.649
Expected rank in adding tasks	2.24	0.77	409	2.31	0.82	123	0.430
Expected experimental earnings	73.84	57.63	409	66.74	50.96	123	0.190
Overconfidence	0.24	0.63	409	0.21	0.76	123	0.697
Risk aversion coefficient	4.74	4.41	409	3.87	4.79	123	0.074
Non-competitive tournament	0.41	0.49	409	0.44	0.50	123	0.513
Fraction of women	0.30	0.46	409	0.34	0.48	129	0.388
Additional control variables							
Age	28.22	2.44	409	28.93	2.72	129	0.009
Fraction non-white	0.55	0.50	409	0.64	0.48	129	0.062
Fraction US residents	0.77	0.42	409	0.74	0.44	129	0.584
Fraction married before MBA	0.26	0.44	409	0.22	0.41	129	0.362
Fraction religious	0.47	0.50	409	0.42	0.50	129	0.312
GMAT Quantitative percentile	81.91	12.81	406	80.84	16.06	129	0.489
GMAT Verbal percentile	88.02	11.45	406	85.31	12.75	129	0.033
GMAT Analytic percentile	71.91	21.75	383	68.70	22.63	112	0.184
GPA	3.33	0.34	391	3.18	0.42	99	0.002
CRT score	2.44	1.33	409	2.43	1.35	129	0.979
RMET score	0.75	0.10	409	0.74	0.10	129	0.469
Discount rate	0.05	0.04	376	0.05	0.04	108	0.718
Trust	0.38	0.30	409	0.34	0.29	123	0.453
Reciprocity	0.36	0.20	409	0.33	0.20	123	0.151
Cooperation	0.33	0.47	409	0.29	0.46	123	0.436
Survey overconfidence	0.90	4.56	391	1.92	4.42	99	0.044
Survey risk (general)	6.44	1.89	409	6.57	2.19	129	0.541
Survey risk (monetary)	1.49	1.01	409	1.62	0.95	129	0.182

nament choice as the dependent variable. In line with the regressions in Table II, as independent variables, we include the participants' gender, performance, overconfidence, and risk aversion coefficient. In addition, we also add a dummy variable equal to one for participants who did not fully consent. We find that the estimated marginal effect of the dummy variable is minimal (0.003) and is not statistically significant (p = 0.957).

IAII. Attrition in the 2015 follow-up survey

Of the 409 participants who consented to the analysis of their data in 2006, 263 (64.3%) answered the follow-up survey in 2015. To evaluate whether the 263 survey respondents differ from the nonresponding 146 participants, in the top part of Table IAII, we present the means and standard deviations of the variables in Table I for which we have data for both samples. For each variable, the table also displays the p-value obtained when we test whether the two samples are significantly different from each other (t-tests for continuous variables and χ^2 tests for categorical variables). In the bottom part of Table IAII, we present the same information for the control variables we will use for the robustness checks in Section III. We describe these variables and how we collected them in Section IAV.

For most variables, there are no statistically significant differences between the participants who answered the survey and those who did not. If we use an unadjusted significance threshold of 5%, then we find a significant difference in three out of the fifteen variables in the top part of Table IAII (overconfidence, one-off bonuses, and gender) and in six out of the nineteen variables in the bottom part of Table IAII (donations to University of Chicago, discount rate, fraction of US residents, fraction of white individuals, GMAT verbal percentile, and CRT scores). However, if we account for multiple comparisons by adjusting p-values with the Benjamini-Hochberg method, none of the variables shows a significant difference between the participants who answered the survey and those who did not.

We also test whether preferences for competition differ between participants who consented to the analysis of all their data and those who did not. To do so, we run a probit regression with the participants' tournament choice as the dependent variable and the participants' gender, performance, overconfidence, and risk aversion coefficient as independent variables. In addition, we also included a dummy variable equal to one for participants who did not respond to the follow-up survey. We find that the estimated marginal effect of the dummy variable is small (0.022) and is not statistically significant ($p = 0.690$).

In conclusion, although there is no clear-cut evidence of strong selection effects in responding to the follow-up survey, there might be reasons for worry. In particular, if we do not correct p-values for multiple testing, we see significant differences in three important variables for the paper: overconfidence, one-off bonuses, and gender. Moreover, although the difference is not statistically

Table IAII. Summary statistics depending on responding to the follow-up survey in 2015

This table reports means, standard deviations, and number of observations for variables of interest. The rightmost column displays p-values from tests of equality of distributions between people who responded to the follow-up survey in 2015 and those who did not (t-tests for ordinal variables and χ^2 tests for categorical variables).

	Respondent			Non-respondent			
	mean	*s.d.*	*N*	*mean*	*s.d.*	*N*	$p - value$
Competitive	0.52	0.50	263	0.52	0.50	146	0.994
Performance	2.43	0.78	263	2.58	0.76	146	0.063
Expected rank in adding tasks	2.25	0.78	263	2.23	0.76	146	0.735
Expected experimental earnings	76.91	60.41	263	68.31	51.98	146	0.132
Overconfidence	0.18	0.63	263	0.35	0.64	146	0.008
Risk aversion coefficient	4.52	4.40	263	5.13	4.42	146	0.182
Non-competitive tournament	0.41	0.49	263	0.40	0.49	146	0.957
Fraction of women	0.27	0.44	263	0.36	0.48	146	0.041
Total income in 2008	180.77	161.02	263	164.11	144.32	146	0.284
Base salary in 2008	108.15	18.65	263	105.40	16.62	146	0.127
Total bonus in 2008	72.63	153.66	263	58.70	140.26	146	0.354
One-off bonus in 2008	43.65	30.50	263	37.30	24.37	146	0.022
Guaranteed performance bonus in 2008	28.98	144.84	263	21.40	137.19	146	0.600
Working in finance in 2008	0.50	0.50	263	0.53	0.50	146	0.621
Working in consulting in 2008	0.26	0.44	263	0.22	0.42	146	0.375
Additional control variables							
Age	28.04	2.30	263	28.54	2.65	146	0.057
Fraction non-white	0.50	0.50	263	0.64	0.48	146	0.005
Fraction US residents	0.81	0.39	263	0.68	0.47	146	0.003
Fraction married before MBA	0.25	0.43	263	0.27	0.45	146	0.552
Fraction religious	0.48	0.50	263	0.45	0.50	146	0.600
GMAT Quantitative percentile	81.34	12.61	262	82.96	13.14	144	0.228
GMAT Verbal percentile	89.34	9.80	262	85.61	13.67	144	0.004
GMAT Analytic percentile	73.47	21.34	245	69.13	22.27	138	0.064
GPA	3.35	0.34	255	3.29	0.35	136	0.072
CRT score	2.54	1.33	263	2.26	1.32	146	0.045
RMET score	0.75	0.10	263	0.74	0.10	146	0.120
Discount rate	0.05	0.04	244	0.06	0.05	132	0.002
Trust	0.38	0.30	263	0.40	0.30	146	0.346
Reciprocity	0.36	0.20	263	0.37	0.21	146	0.616
Cooperation	0.35	0.48	263	0.30	0.46	146	0.358
Survey overconfidence	0.93	4.51	255	0.85	4.66	136	0.858
Survey risk (general)	6.54	1.83	263	6.26	1.98	146	0.155
Survey risk (monetary)	1.46	1.02	263	1.53	1.01	146	0.526
Donations to U. of Chicago	196.74	207.20	263	154.12	184.49	146	0.033

significant, the total income in 2008 of respondents to the survey is noticeably higher than that of non-respondents ($17K or 10% more). For this reason, in Section IAIII, we perform a series of robustness checks where we account for selection into the follow-up survey.

IAIII. Robustness checks

A. Gender differences in preferences for competition

A.1. Measurement error and misspecification

Our first robustness check addresses concerns about using a residual measure for preferences for competition (Gillen et al., 2019; van Veldhuizen, 2022). As Niederle and Vesterlund (2007), we measure preferences for competition by looking at whether individuals choose a tournament payment scheme. However, since there are several reasons why an individual might choose tournament pay, we interpret the choice of tournament pay as indicating stronger preferences for competition only after we control for the individual's performance, overconfidence, and risk aversion. This way of measuring preferences for competition has recently come under scrutiny because it is not a direct measure of the trait of interest. More precisely, if there is measurement error in the control variables or they are incorrectly specified in the regression, it is possible for there to be a bias in the estimated effects of preferences for competition.

If the concerns raised by Gillen et al. (2019) are valid in our data, they could steer us toward incorrect inferences. First, in regressions where we evaluate whether there are gender differences in preferences for competition (Table II), a significant coefficient on the gender dummy might be due to (residual) gender differences in risk aversion or overconfidence and might not be due to differences in preferences for competition. Second, in regressions where we test the effect of preferences for competition on income, a significant coefficient on the competitive dummy might again be due to (residual) effects of risk aversion or overconfidence. In this subsection, we take a closer look at the identification of gender differences in preferences for competition. In Subsection B below, we do the same for the effect of preferences for competition on income.

To evaluate whether there is bias in the identification of gender differences in preferences for competition, we reran the probit regressions in Table II with additional control variables. We report the resulting marginal effects in Table IAIII. In column (1), we simply reproduce the last regression of Table II, where we regress the participants' choice between tournament and piece-rate pay on the participants' gender, performance, overconfidence, and risk preferences. In this regression, there is a significant gender gap in the choice of tournament pay of 14.8% ($p = 0.013$), which we in-

Table IAIII. Robustness of the gender gap in preferences for competition to measurement error and misspecification

This table presents regressions of the choice of tournament pay. Marginal effects from probit regressions are reported with standard errors in parentheses. ***, **, and * indicate statistical significance at the 0.01, 0.05, and 0.10 level, respectively.

	(1)	(2)	(3)	(4)
Woman	-0.148^{**}	-0.183^{***}	-0.147^{**}	-0.170^{**}
	(0.060)	(0.061)	(0.064)	(0.066)
Obs.	409	409	409	409
χ^2 test	97.111	120.033	95.530	117.982

terpret in the paper as a gender difference in preferences for competition. Given the large number of dummy variables in subsequent regressions, we limit the table to the coefficient on the gender dummy.

In column (2), we control for the original control variables nonparametrically. Specifically, we split each control variable into 6 equally sized bins (sextiles), which we introduce as dummy variables. Introducing these variables allows us to capture nonlinear relations between choosing tournament pay and performance, risk aversion, and overconfidence, which can be a source of bias in the identification of gender differences in the preferences for competition.[1] As can be seen in Table IAIII, the coefficient on the gender dummy increases by 4.6 percentage points to 18.3% and remains statistically significant (p = 0.003).

In column (3), we use answers to the initial survey to include additional measures of the participants' risk aversion and overconfidence. These variables are bound to be noisier than our lab measures since we did not elicit them with incentive-compatible methods. However, as demonstrated by Gillen et al. (2019), they can capture some of the potential measurement error of the incentive-compatible variables. For risk aversion, we use a commonly used survey measure of general attitudes toward risk (Falk et al., 2018) and another self-reported measure of risk attitudes in the monetary domain. For overconfidence, we use the participants' expected GPA decile (estimated in 2006) minus their actual GPA decile (in 2008). We provide descriptive statistics for these variables in Tables IAI and IAII and a detailed description in Section V below. Once again, the coefficient on the gender dummy is robust to the introduction of all these variables: it decreases by 0.1 percentage points to 14.7% (p = 0.022).

Finally, in column (4), we include all the additional control variables from the regressions in columns (2) and (3). Compared to the regression in column (1), we find an increase in the gen-

[1]We also tried specifications using the squared value of the control variables. We obtain very similar results.

Table IAIV. Robustness of the gender gap in preferences for competition to additional controls

This table presents regressions of the choice of tournament pay. Marginal effects from probit regressions are reported with standard errors in parentheses. ***, **, and * indicate statistical significance at the 0.01, 0.05, and 0.10 level, respectively.

	(1)	(2)	(3)
Woman	−0.148**	−0.118*	−0.138*
	(0.060)	(0.065)	(0.073)
Obs.	409	409	409
χ^2 test	97.111	112.657	145.328

der coefficient on 2.2 percentage points to 17.0% (p = 0.010). Hence, overall, we do not find evidence that the gender difference in preferences for competition is due to measurement error or misspecification.

A.2. Additional control variables

Here, we test the robustness of the gender difference in preferences for competition to the inclusion of a large set of control variables. Specifically, we include all the 15 additional control variables seen in Tables IAI and IAII. These variables include demographic characteristics (e.g., age, race, residence, marital status, religiosity), measures of different kinds of abilities (e.g., mathematical, verbal, and analytical skills, capacity for cognitive reflection, and emotional intelligence), and other standard experimental measures (e.g., willingness to trust, reciprocate, and cooperate with others). We describe all these variables in detail in Section IAV below. This exercise allows us to evaluate whether preferences for competition describe variation between individuals that is not captured by typically measured observables. In addition, if risk aversion and overconfidence affect variables such as GMAT scores, trust, and cooperation, then the inclusion of these variables should reduce the effects of measurement error (as reasoned above).

The impact of including all these control variables on the gender dummy is seen in Table IAIV. As above, in column (1), we simply reproduce the last regression of Table II. In column (2), we include the 15 additional control variables, while in column (3), we also add the variables used in column (4) of Table IAIII to reduce bias due to measurement errors and misspecification. We can see that the inclusion of all these control variables has a moderate effect on the magnitude of the gender gap in tournament pay. In column (2), it shrinks by 2.9 percentage points (around 0.47 standard errors) to 11.9% (p = 0.069) and by 1.0 percentage points (around 0.16 standard errors) to 13.8% (p = 0.057).

We think that this is compelling evidence that, by and large, competitiveness captures individual variation that would otherwise remain unobserved. Moreover, even though the shrinking of the gender gap (and the increase in its *p*-value) might suggest that there is a bias due to measurement error, we should point out that these regressions are not as appropriate to test measurement error as the regressions in Table IAIII (where the coefficient does not shrink). The reason is that the variables in Table IAIII are measures of risk preferences and overconfidence unrelated to preferences for competition. In contrast, the additional control variables in these regressions could be related to this trait. For instance, it is conceivable that preferences for competition, which have been shown to affect educational choices (Buser et al., 2014; Reuben et al., 2017), have a direct effect on variables measuring ability, such as GMAT scores, which would also explain the attenuation of the coefficient.

A.3. Preferences for high rewards

Recall that, like in the third period of the experiment, in the fourth period, participants had to choose whether they wanted to be compensated for their past performance according to the piece rate or tournament payment schemes. Unlike in the third period, however, they did not have to perform the adding task again as their decision applied to their past piece-rate performance. As Niederle and Vesterlund (2007) argue this decision is akin to a choice between a certain payoff and a lottery with ambiguous probabilities and is not affected by the participants' attitudes towards competition. If this is the case, it is interesting to check whether men and women choose differently in this period and, if they do, whether these differences help us account for the gender difference in preferences for competition.

Columns (1) through (3) of Table IAV reproduce the regressions of Table II but use as the dependent variable a dummy variable that equals one if the participant chooses tournament pay in the fourth period of the experiment. We label this variable noncompetitive tournament. Without any controls (column (1)), the gender gap in choosing the noncompetitive tournament equals 22.0%. Controlling for the participants' performance reduces the gender gap by 4.5 percentage points to 17.5% (column (2)). Further controlling for the participants' overconfidence and risk preferences reduces the gender gap to 10.4% (column (3)). Hence, like with the decision to compete, gender plays a role in choosing noncompetitive tournament pay.

For our paper, more important is to test whether the participants' choice of noncompetitive tournament pay explains the gender gap in choosing the competitive tournament (reported in Table II), which we interpret as a gender difference in preferences for competition. Columns (4) and (5) of Table IAV contain regressions that use the competitive dummy as the dependent variable. In column (4), we reproduce the last regression of Table II, where the decision to compete is explained

Table IAV. Gender gap in preferences for competition and preferences for high rewards

This table presents regressions of the choice of tournament pay in the fourth period of the experiment (columns (1), (2), and (3)) and the choice of tournament pay in the third period of the experiment (columns (4) and (5)). Marginal effects from probit regressions are reported with standard errors are in parentheses. ***, **, and * indicate statistical significance at the 0.01, 0.05, and 0.10 level, respectively.

	(1)	(2)	(3)	(4)	(5)
Woman	−0.220***	−0.175***	−0.104*	−0.148**	−0.133**
	(0.049)	(0.052)	(0.058)	(0.060)	(0.064)
Performance		0.154***	0.267***	0.272***	0.209***
		(0.026)	(0.032)	(0.034)	(0.036)
Overconfidence			0.217***	0.203***	0.152***
			(0.032)	(0.033)	(0.034)
Risk aversion			−0.056**	−0.083***	−0.073**
			(0.027)	(0.028)	(0.029)
Non-competitive tournament					0.330***
					(0.056)
Obs.	409	409	409	409	409
χ^2 test	17.355	49.866	96.974	97.111	129.076

by the participants' performance, overconfidence, and risk aversion. In column (5), we add the noncompetitive dummy as an independent variable. We can see that even though the coefficient on the noncompetitive dummy is statistically significant, controlling for this variable does not have a remarkable effect on the gender gap in the decision to compete. The coefficient on the gender dummy shrinks by 1.5 percentage points but is still economically and statistically significant. This result supports our conclusion that there is a gender difference in preferences for competition among our participants.

B. Effect of preferences for competition on income in 2008

Next, we provide a series of robustness checks for the effect of preferences for competition on income in 2008 (reported in Table V). Throughout this subsection, we focus solely on regressions without industry fixed effects to keep the number and size of the tables at a reasonable level. In line with the main body of the paper, our results do not change much if we control for industry. We can provide the regressions with industry fixed effects upon request.

Table IAVI. Robustness of the effect of preferences for competition on income in 2008 to measurement error and misspecification

This table presents regressions of the log of total income in 2008 in column (1), the log of base salary in 2008 in column (2), a hurdle model of the likelihood of receiving a bonus in column (3) and its magnitude in column (4), and a hurdle model of the likelihood of receiving a guaranteed performance bonus in column (5) and its magnitude in column (6). Linear estimates are reported in columns (1), (2), (3), and (5). Marginal effects are reported in columns (4) and (6). Standard errors are in parentheses. ***, **, and * indicate statistical significance at the 0.01, 0.05, and 0.10 level, respectively.

	Total	*Base*	Total bonus		Perform. bonus	
	income	*salary*	*Obtain*	*Size*	*Obtain*	*Size*
	(1)	(2)	(3)	(4)	(5)	(6)
Woman	−0.088**	−0.004	0.034	−0.331***	−0.057	−0.546**
	(0.038)	(0.018)	(0.026)	(0.083)	(0.061)	(0.261)
Competitive	0.074**	0.018	0.012	0.162**	0.011	0.547***
	(0.036)	(0.017)	(0.024)	(0.079)	(0.057)	(0.211)
Obs.	409	409	409	380	409	153
F-test/χ^2 test	2.118	1.431	24.253	52.907	24.132	27.153
R^2	0.098	0.069				

B.1. Measurement error and misspecification

We start by examining whether the effect of preferences for competition on income in 2008 is overestimated due to measurement error or misspecification of the control variables (Gillen et al., 2019). Similar to Subsection B above, in Table IAVI, we reran the more interesting regressions from Table V, adding the two survey measures of risk aversion and overconfidence (see Tables IAI and IAII for descriptive statistics of these variables and Section IAV below for a detailed description), as well as substituting performance, risk aversion, and overconfidence with their respective 6 dummy variables. For space considerations, we limit the table to the coefficients on the gender and competitive dummies.

In column (1), the dependent variable is the log of total income in 2008. The inclusion of the control variables slightly decreases the coefficient on the competitive dummy from 0.079 to 0.074, but it remains both economically and statistically significant. In column (2), the dependent variable is the log of base salaries in 2008. The additional control variables do not change the result of no relationship between base salaries and preferences for competition (the coefficient on the competitive dummy remains unchanged at 0.022 and remains statistically insignificant). In columns (3) and (4), we reran the two-step hurdle model used to estimate the probability of getting a bonus (column (3)) and the magnitude of the bonus received (column (4)). In columns (5) and (6), we repeat the same regression but solely for guaranteed performance bonuses. Once again, we do not find that the inclusion of the control variables negatively impacts the coefficient on the competitive dummy. It changes from 0.158 to 0.162 when considering the magnitude of all bonuses and from 0.571 to 0.547 when considering the magnitude of guaranteed performance bonuses.

In summary, we do not find evidence that the relationship between the various forms of income in 2008 and the competitive dummy is due to measurement error or misspecification, which suggests that it is indeed driven by preferences for competition.

B.2. Additional control variables

Here, we test the robustness of the effect of preferences for competition on income in 2008 to the inclusion of a large set of control variables. Like in Subsection A above, in Table IAVII, we reran a selection of the regressions from Table V, including the 15 additional control variables seen in Tables IAI and IAII (described in Section IAV below). These variables include demographic characteristics (e.g., age, race, residence, marital status, religiosity), measures of different kinds of abilities (e.g., mathematical, verbal, and analytical skills, capacity for cognitive reflection, and emotional intelligence), and other common experimental measures (e.g., willingness to trust, reciprocate, and cooperate with others). This robustness check lets us evaluate whether preferences for competition describe variation in income that is not captured by typically measured observables. Once again, we limit the table to the coefficients on the gender and competitive dummies.

In column (1), the dependent variable is the log of total income in 2008. Including the additional control variables does not affect the coefficient on the competitive dummy (it changes from 0.079 to 0.078, which is less than 0.03 standard errors). In column (2), the dependent variable is the log of base salaries in 2008. The additional control variables do not modify the result of no relationship between base salaries and preferences for competition (the coefficient changes from 0.022 to 0.024 and remains statistically insignificant). In columns (3) and (4), we reran the two-step hurdle model used to estimate the probability of getting a bonus (column (3)) and the magnitude of the bonus received (column (4)). In columns (5) and (6), we repeat the same regression but solely for the guaranteed performance bonuses. Once again, we do not find that the inclusion of the control variables has a large effect on the coefficient on the competitive dummy. It slightly decreases from 0.158 to 0.152 (less than 0.08 standard errors) when considering the magnitude of all bonuses and from 0.571 to 0.528 (from $13K to $12K, around 0.20 standard errors) when considering the magnitude of guaranteed performance bonuses.

In summary, we do not find that the relationship between preferences for competition and income in 2008 is affected by including a large set of control variables. Therefore, it seems likely

Table IAVII. Robustness of the effect of preferences for competition on income in 2008 to additional controls

Regressions of the log of total income in 2008 in column (1) and of the log of base salary in 2008 in column (2). Hurdle model of the likelihood of receiving a bonus in column (3) and its magnitude in column (4). Hurdle model of the likelihood of receiving a guaranteed performance bonus in column (5) and its magnitude in column (6). Linear estimates in columns (1), (2), (3), and (5). Marginal effects in columns (4) and (6). Standard errors are in parentheses.

	Total	*Base*	Total bonus		Perform. bonus	
	income	*salary*	*Obtain*	*Size*	*Obtain*	*Size*
	(1)	(2)	(3)	(4)	(5)	(6)
Woman	−0.087**	0.007	0.035	−0.356***	−0.051	−0.575**
	(0.038)	(0.018)	(0.026)	(0.085)	(0.062)	(0.248)
Competitive	0.077**	0.024	0.006	0.150*	0.035	0.524**
	(0.036)	(0.017)	(0.024)	(0.080)	(0.058)	(0.213)
Obs.	409	409	409	380	409	153
F-test/χ^2 test	2.640	1.800	32.12	48.042	30.995	32.374
R^2	0.120	0.085				

that preferences for competition explain variance in earnings that would otherwise remain unexplained.

B.3. Preferences for high rewards

In this subsection, we analyze the effect of choosing tournament pay without having to perform under competitive conditions. Niederle and Vesterlund (2007) posit that this decision is unaffected by the participants' preferences for competition. If this is the case, it is interesting to analyze whether this variable is also a good predictor of the participants' income in 2008. To test the effect of a 'preference for high rewards,' we reran a selection of the regressions from Table V, including the noncompetitive tournament dummy in Table IAVIII. In columns (1) through (4), we use the noncompetitive tournament dummy instead of the competitive dummy. In columns (5) through (8), we use both the noncompetitive tournament and competitive dummies. Once again, we limit the table to the coefficients on the gender and competitive dummies.

In columns (1) and (5), the dependent variable is the log of total income in 2008. When the noncompetitive tournament dummy is included alone (in column (1)), its coefficient is positive but is less than half the coefficient on competitive in Table V (0.036 vs. 0.079, which is a difference of around one standard error), and it is not statistically different from zero (p = 0.322). When both the noncompetitive tournament and competitive dummies are included, the coefficient on competitive

Table IAVIII. Income in 2008 and preferences for competition or for high rewards

This table presents regressions of the log of total income in 2008 in columns (1) and (5), the log of base salary in 2008 in columns (2) and (6), a hurdle model of the likelihood of receiving a bonus in columns (3) and (7), and of its magnitude (in logs) in columns (4) and (8). Linear estimates are reported in columns (1), (2), (4), (5), (6), and (8). Marginal effects are reported in columns (3) and (7). Standard errors are in parentheses. ***, **, and * indicate statistical significance at the 0.01, 0.05, and 0.10 level, respectively.

	Total income	*Base salary*	Total bonus *Obtain*	Total bonus *Size*	*Total income*	*Base salary*	Total bonus *Obtain*	Total bonus *Size*
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Woman	−0.114***	−0.010	0.031	−0.397***	−0.106***	−0.009	0.033	−0.379***
	(0.036)	(0.016)	(0.029)	(0.079)	(0.036)	(0.017)	(0.029)	(0.079)
Non-competitive	0.036	0.027	−0.015	0.019	0.014	0.023	−0.020	−0.032
tournament	(0.036)	(0.017)	(0.029)	(0.081)	(0.038)	(0.018)	(0.030)	(0.085)
Competitive					0.075**	0.015	0.019	0.167**
					(0.038)	(0.017)	(0.031)	(0.083)
Obs.	409	409	409	380	409	409	409	380
F-test/χ^2 test	2.886	1.161	3.769	27.786	3.088	1.092	4.163	32.141
R^2	0.035	0.014						

is economically and statistically significant (around $12K, p = 0.046). By contrast, the coefficient on the noncompetitive tournament is small and far from statistical significance (around $2K, p = 0.709). In columns (2) and (6), the dependent variable is the log of base salaries in 2008. Consistent with the results reported in the main body of the paper, neither the coefficient on noncompetitive tournament nor of competitive display a significant association with base salaries. Finally, in columns (3) and (4), as well as (7) and (8), we reran the two-step hurdle model used to estimate both the probability of getting a bonus (columns (3) and (7)) and the magnitude of the bonus received (columns (4) and (8)). Once again, we do not find that the noncompetitive tournament dummy is significantly associated with the magnitude of the bonus, while the competitive dummy is.

In summary, we find compelling evidence that the coefficient on the competitive dummy variable is indeed capturing a relationship between the participants' preferences for competition and income that is not related to the choice of a tournament payment scheme *per se*.

B.4. Guaranteed performance bonus

In this subsection, we test the robustness of the results for the guaranteed performance bonus component. Recall that we group the various bonuses into two components: the one-off bonus component, which includes relocation, tuition, sign-on, and retention bonuses, and the guaranteed

Table IAIX. Robustness of the guaranteed performance bonus to the exclusion of bonuses classified as "other"

This table presents a hurdle model of the likelihood of receiving a guaranteed performance bonus in column (1) and of its magnitude (in logs) in column (2). Marginal effects are reported in column (1) and linear estimates in column (2). Standard errors are in parentheses. ***, **, and * indicate statistical significance at the 0.01, 0.05, and 0.10 level, respectively.

	Obtain	*Size*
	(1)	(2)
Woman	−0.029	−0.474**
	(0.053)	(0.242)
Competitive	0.043	0.461**
	(0.055)	(0.225)
Obs.	409	128
χ^2 test	1.375	12.190

performance bonus component, which includes stock options, profit sharing, guaranteed performance, and other bonuses. Since it is not entirely clear what bonuses are classified as "other" in Table IAIX, we reran the two-step hurdle model used to estimate both the probability of getting some guaranteed performance bonus (column (6) in Table V) and the magnitude of the guaranteed performance bonus (column (7) in Table V) excluding "other" bonuses. The exclusion of other bonuses decreases the coefficient on the competitive dummy from 0.571 to 0.461 when considering the magnitude of the guaranteed performance bonus, but it remains large and statistically significant. The exclusion of other bonuses also leaves unchanged the lack of a significant correlation between receiving some guaranteed performance bonus and being competitive.

B.5. Boasting

In this subsection, we analyze the correlation between boasting and income in 2008 (and 2015). As mentioned in the main body of the paper, two years after the initial experiment, 95 of the MBAs in our sample participated in another study. In that experiment, they were asked, in private, to recall the number of additions they had answered correctly. Subsequently, they were asked to communicate that number to a group of colleagues. We use the difference between the recalled performance and the performance communicated to others as a measure of boasting. The details for this experiment are available in Reuben et al. (2012).

In Table IAX, we look at the effect of boasting on income in 2008 (and 2015). Column (1) reruns the baseline specification from Table V using only the 95 MBAs who participated in the second ex-

Table IAX. Determinants of income controlling for propensity to boast

This table presents regressions of the log of total income in 2008 in columns (1) to (3) and the log of total income in 2015 in columns (4) to (6). The regressions in columns (2), (3), (5), and (6) restrict the sample to participants for whom we measured the propensity to boast. Overconfidence, risk aversion, and boasting are standardized to have a mean of zero and a standard deviation of one. All regressions include performance as a control. Linear estimates are reported with standard errors in parentheses. ***, **, and * indicate statistical significance at the 0.01, 0.05, and 0.10 level, respectively.

	Total income in 2008			Total income in 2015		
	(1)	(2)	(3)	(4)	(5)	(6)
Woman	−0.116	−0.114	−0.117	−0.171	−0.231	−0.205
	(0.076)	(0.075)	(0.076)	(0.218)	(0.223)	(0.219)
Competitive	0.043	0.043	0.047	−0.024	−0.046	−0.003
	(0.069)	(0.066)	(0.069)	(0.180)	(0.180)	(0.182)
Risk aversion	−0.041	−0.035	−0.036	−0.049	−0.029	−0.039
	(0.033)	(0.033)	(0.033)	(0.085)	(0.089)	(0.086)
Overconfidence	−0.010		−0.008	0.102		0.113
	(0.035)		(0.035)	(0.103)		(0.103)
Boasting		−0.035	−0.035		−0.126	−0.166
		(0.030)	(0.031)		(0.144)	(0.139)
Competitive ×				−0.419**		−0.461***
Overconfidence				(0.167)		(0.169)
Competitive ×					0.179	0.251
Boasting					(0.169)	(0.165)
Obs.	95	95	95	73	73	73
F-test	1.154	1.423	1.182	1.598	0.677	1.498
R^2	0.061	0.074	0.075	0.127	0.058	0.158

periment. Column (2) runs the same specification, but it substitutes the measure of overconfidence with the measure of boasting. Column (3) includes both the overconfidence and the boasting measures. Columns (4), (5), and (6) do the same exercise but using the log of income in 2015 as the dependent variable. In these regressions, we start with the baseline regression of Table VIII, which includes the interaction between overconfidence and preferences for competition. We use this specification since it is the one that displays a significant effect for preferences for competition.

Comparing the baseline regression of Table V to that in column (2), we see that the gender coefficient is roughly the same in both regressions, but the coefficient on preferences for competition is roughly half in the smaller sample. It is also evident from the large standard errors that we do not have sufficient power to reach clear conclusions. That being said, comparing column (1) with columns (2) and (3) is still illustrative of the impact of using the boasting variable as a control. In columns (2) and (3), we can see that the coefficient on the boasting variable is negative. In addition, introducing boasting does not reduce the size of the coefficient on preferences for competition (compared to column (1)). In other words, there is no support for the idea that boasting is responsible for the positive relationship between preferences for competition and income in 2008. The results for income in 2015 are analogous. Remarkably, the interaction between overconfidence and preferences for competition is still statistically significant in the reduced sample (column (4)). In columns (5) and (6), the coefficient on boasting is negative, and its introduction has no effect on the interaction between overconfidence and preferences for competition (column (6)). Hence, once again, we do not find evidence that the association between preferences for competition and income in 2015 is impacted by a tendency to boast.

C. Effect of preferences for competition on income in 2015

Next, we provide a series of robustness checks for the effect of preferences for competition on income in 2015. Once again, we focus on regressions without industry fixed effects since results do not change much by controlling for industry (regressions with industry fixed effects are available upon request).

C.1. Attrition in the 2015 follow-up survey

As reported in Section IAII above, there is some evidence of selection into the 2015 follow-up survey. With *p*-values uncorrected for multiple comparisons, we find significant differences in 3 important variables: overconfidence, one-off bonuses, and gender. Hence, in Table IAXI, we re-estimated regressions from Tables VII and VIII, correcting for selection into the follow-up survey using Heckman's two-step procedure (Heckman, 1979).[2] Panel A shows the coefficients on the second stages, while Panel B shows the coefficients on the respective first stages.

In the first stage, we include the same independent variables as in the second stage (i.e., competitive and gender dummies, overconfidence, risk aversion, and performance). In addition, to limit potential problems caused by collinearity between the correction term and the independent variables, we include two exclusion restrictions (Puhani, 2000). The first exclusion restriction is the log of participants' donations to the class gift to the University of Chicago. As we saw in Section

[2]We obtain similar results we maximum likelihood estimates. Also, note that 263 individuals answered the 2015 follow-up survey. However, among the respondents there were 13 who were not employed. Since our dependent variable is employment income, we dropped these individuals from the analysis. However, including them gives very similar results.

Table IAXI. Robustness of the effect of preferences for competition and overconfidence on income in 2015 to selection into the follow-up survey

This table presents regressions of the log of total income in 2015 in columns (1) and (2), the log of base salary in 2015 in columns (3) and (4), and the log of the performance bonus in 2014 in columns (5) and (6). Panel A contains linear estimates corrected for selection into the follow-up survey using Heckman's two-step procedure. Panel B reports the marginal effects of the respective selection equations. Standard errors are in parentheses. ***, **, and * indicate statistical significance at the 0.01, 0.05, and 0.10 level, respectively.

	Total income		Base salary		Bonus size	
	Panel A: Selection-corrected estimates					
	(1)	(2)	(3)	(4)	(5)	(6)
Woman	−0.426***	−0.427***	−0.237***	−0.238***	−0.915***	−0.925***
	(0.129)	(0.127)	(0.088)	(0.087)	(0.262)	(0.259)
Competitive	0.026	0.028	−0.005	−0.005	0.104	0.073
	(0.099)	(0.098)	(0.068)	(0.068)	(0.201)	(0.200)
Overconfidence	−0.097	−0.006	−0.068*	−0.031	0.018	0.198
	(0.059)	(0.072)	(0.040)	(0.050)	(0.130)	(0.149)
Competitive ×		−0.214**		−0.087		−0.435**
Overconfidence		(0.088)		(0.061)		(0.179)
Risk aversion	−0.114**	−0.108**	−0.063**	−0.061*	−0.098	−0.091
	(0.047)	(0.046)	(0.032)	(0.032)	(0.097)	(0.096)
	Panel B: Selection into the survey					
	(1)	(2)	(3)	(4)	(5)	(6)
Woman	−0.132**	−0.132**	−0.132**	−0.132**	−0.145***	−0.145***
	(0.052)	(0.052)	(0.052)	(0.052)	(0.055)	(0.055)
Competitive	−0.034	−0.035	−0.034	−0.035	−0.040	−0.041
	(0.054)	(0.054)	(0.054)	(0.054)	(0.057)	(0.057)
Overconfidence	−0.054**	−0.066*	−0.054**	−0.066*	−0.076***	−0.076**
	(0.028)	(0.035)	(0.028)	(0.035)	(0.029)	(0.036)
Competitive ×		0.027		0.027		0.002
Overconfidence		(0.048)		(0.048)		(0.050)
Risk aversion	−0.032	−0.031	−0.032	−0.031	−0.040	−0.040
	(0.024)	(0.024)	(0.024)	(0.024)	(0.025)	(0.025)
Discount rate	−0.072***	−0.071***	−0.072***	−0.071***	−0.080***	−0.079***
	(0.023)	(0.024)	(0.023)	(0.024)	(0.025)	(0.025)
Donations to	0.048**	0.049**	0.048**	0.049**	0.041*	0.041*
U. of Chicago	(0.023)	(0.023)	(0.023)	(0.023)	(0.024)	(0.024)
Uncensored obs.	396	396	396	396	364	364
Censored obs.	146	146	146	146	146	146
χ^2 test	17.030	25.734	11.618	14.956	21.463	27.976

II above, the more money a student donated to the class gift, the more likely they are to respond to the follow-up survey (a one standard deviation increase in donations predicts a 5.6 percentage point increase in the probability of responding to the follow-up survey). This effect is probably due to how much individuals identify with the university and not their income or preferences for competition. The second exclusion restriction is the participants' elicited discount rate. Higher discount rates are strongly associated with a lower likelihood of responding to the follow-up survey (a one standard deviation increase in the discount rate predicts a 7.3 percentage point decrease in the probability of responding to the follow-up survey). This association is most likely an effect of discount rates, which have been linked theoretically and empirically to procrastination in filling out questionnaires (O'Donoghue and Rabin, 1999; Reuben et al., 2015), that is unrelated to income in 2015 or preferences for competition.[3]

In columns (1) and (2), the dependent variable of the second stage is the log of total income in 2015. Correcting for selection into the follow-up survey slightly decreases the coefficient on the competitive dummy (by around 1 log point in column (1) and 3 log points in column (2)). The coefficient on overconfidence is similar in magnitude but is no longer significant in the specification of column (1). However, the interaction between overconfidence and competitive remains negative, large, and highly statistically significant. Hence, we conclude that selection into the follow-up survey had little effect on the estimated effects of preferences for competition, overconfidence, and their interaction. It is important to note that these results are not the consequence of a weak first stage (Panel B). Both exclusion restrictions are good predictors of answering the survey. In columns (3) and (4), the dependent variable of the second stage is the log of base salaries in 2015. Correcting for selection into the follow-up survey had a negligible effect on the coefficient on the competitive dummy, overconfidence, and their interaction. In columns (5) and (6), the dependent variable of the second stage is the log of the performance bonus. Note that, to run these regressions, we dropped the survey respondents who did not receive a bonus. For this reason, the coefficients in Table IAXI are not entirely comparable to those in Tables VII and VIII, which are based on a two-step hurdle model. Nonetheless, it is telling that the coefficients on preferences for competition, overconfidence, and the interaction term are similar in both regressions.

Next, we provide a series of robustness checks for the effect of preferences for competition and its interaction with overconfidence on income in 2015 (reported in VIII).

[3]The correlation coefficients between donations to the university or discount rates with either the competitive dummy or total income in 2008 are low (less than 0.056 for donations and 0.010 for discount rates) and are not statistically significant.

Table IAXII. Robustness of the effect of preferences for competition and overconfidence on income in 2015 to measurement error and misspecification

This table presents regressions of the log of total income in 2015 in column (1), the log of base salary in 2015 in column (2), a hurdle model of the likelihood of receiving a bonus in column (3) and of its magnitude (in logs) in column (4), and a regression of income growth (the log of total income in 2015 minus the log of total income in 2008) in column (5). Linear estimates are reported in columns (1), (2), (4), and (5). Marginal effects are reported in column (3). Standard errors are in parentheses. ***, **, and * indicate statistical significance at the 0.01, 0.05, and 0.10 level, respectively.

	Total income	*Base salary*	Bonus *Obtain*	Bonus *Size*	*Income Growth*
	(1)	(2)	(3)	(4)	(5)
Woman	−0.379***	−0.220**	−0.002	−0.947***	−0.264**
	(0.119)	(0.092)	(0.038)	(0.255)	(0.121)
Competitive	0.014	−0.023	−0.020	0.076	−0.048
	(0.093)	(0.061)	(0.034)	(0.179)	(0.100)
Overconfidence	0.009	−0.005	−0.019	0.108	−0.017
	(0.051)	(0.031)	(0.019)	(0.098)	(0.057)
Competitive × Overconfidence	−0.187**	−0.078	−0.043	−0.382**	−0.182**
	(0.082)	(0.055)	(0.029)	(0.157)	(0.086)
Obs.	250	250	250	218	250
F-test/χ^2 test	2.684	1.281	47.248	65.825	1.982
R^2	0.138	0.092			0.111

C.2. Measurement error and misspecification

We start by looking at whether the effect of preferences for competition on income in 2015 is affected by measurement error or misspecification of the control variables. Similar to Subsections A and B above, in Table IAXII, we reran the regressions from Table VIII, adding the two survey measures of risk aversion, the survey measure of overconfidence, and substituting performance and risk aversion with 6 dummy variables. Since we are interested in the interaction between overconfidence and preferences for competition, we did not transform overconfidence into 6 dummy variables. For space considerations, we limit the table to the coefficients on the gender and competitive dummies, overconfidence, and the interaction of overconfidence and the competitive dummy.

In column (1), the dependent variable is the log of total income in 2015. In column (2), the dependent variable is the log of base salaries in 2015. In columns (3) and (4), we reran the two-step hurdle model used to estimate the probability of getting a bonus (column (3)) and the magnitude of the bonus received (column (4)). Lastly, in column (5), the dependent variable is income growth, defined as the log of total income in 2015 minus the log of total income in 2008. Once again, we do not find that the inclusion of the additional variables has an important qualitative effect on the results reported in the paper. The coefficient on the competitive dummy is similar in all regressions, and it never reaches statistical significance. By contrast, the interaction between the competitive dummy and overconfidence is of similar magnitude and statistical significance to the coefficients seen in Table VIII. In short, we do not find evidence that the results concerning income in 2015 are affected by measurement error or misspecification.

C.3. Additional control variables

Next, we test the robustness of the effect of preferences for competition, overconfidence, and their interaction on income in 2015 to the inclusion of a large set of control variables. As in Subsection A above, in Table IAXIII, we reran the regressions from VIII, including the 15 additional control variables seen in Tables IAI and IAII (described in Section IAV below). These variables include demographic characteristics (e.g., age, race, residence, marital status, religiosity), measures of different kinds of abilities (e.g., mathematical, verbal, and analytical skills, capacity for cognitive reflection, and emotional intelligence), and other standard experimental measures (e.g., willingness to trust, reciprocate, and cooperate with others). For space considerations, we limit the table to the coefficients on the gender and competitive dummies, overconfidence, and the interaction of overconfidence and the competitive dummy.

In column (1), the dependent variable is the log of total income in 2015. In column (2), the dependent variable is the log of base salaries in 2015. In columns (3) and (4), we reran the two-step hurdle model used to estimate the probability of getting a bonus (column (3)) and the magnitude of the bonus received (column (4)). Lastly, in column (5), the dependent variable is the log of total income in 2015 minus the log of total income in 2008. Once again, the coefficient on the competitive dummy is not statistically significant in any regression, and the interaction between the competitive dummy and overconfidence is of similar magnitude and statistical significance to the coefficients in VIII. In summary, the relationship between preferences for competition, overconfidence, and their interaction with income in 2015 is unaffected by the inclusion of a large set of control variables.

C.4. Preferences for high rewards

In this subsection, we analyze again the effect of choosing tournament pay without having to perform under competitive conditions, a decision that is arguably unaffected by the participants' preferences for competition. We evaluate the effect of a "preference for high rewards" on the participants' income in 2015 in Table IAXIV. The table presents selected regressions from VIII, including the noncompetitive tournament dummy, which we also interact with overconfidence.

Table IAXIII. Robustness of the effect of preferences for competition and overconfidence on income in 2015 to additional controls

This table presents regressions of the log of total income in 2015 in column (1), the log of base salary in 2015 in column (2), a hurdle model of the likelihood of receiving a bonus in column (3) and of its magnitude (in logs) in column (4), and a regression of income growth, the log of total income in 2015 minus the log of total income in 2008, in column (5). Linear estimates are reported in columns (1), (2), (4), and (5). Marginal effects are reported in column (3). Standard errors are in parentheses. ***, **, and * indicate statistical significance at the 0.01, 0.05, and 0.10 level, respectively.

	Total income	*Base salary*	Bonus *Obtain*	Bonus *Size*	*Income Growth*
	(1)	(2)	(3)	(4)	(5)
Woman	-0.381^{***}	-0.216^{**}	-0.043	-0.795^{***}	-0.289^{**}
	(0.130)	(0.099)	(0.045)	(0.274)	(0.131)
Competitive	0.039	0.013	0.004	0.045	-0.026
	(0.095)	(0.064)	(0.037)	(0.165)	(0.108)
Overconfidence	0.014	-0.007	-0.038	0.138	-0.022
	(0.056)	(0.033)	(0.030)	(0.111)	(0.059)
Competitive × Overconfidence	-0.223^{***}	-0.112^{**}	-0.043	-0.461^{***}	-0.206^{**}
	(0.083)	(0.056)	(0.038)	(0.171)	(0.085)
Obs.	250	250	250	218	250
F-test/χ^2 test	3.478	1.397	38.527	67.747	1.886
R^2	0.177	0.109			0.112

In column (1), the dependent variable is the log of total income in 2015. In column (2), the dependent variable is the log of base salaries in 2015. In columns (3) and (4), we reran the two-step hurdle model used to estimate the probability of getting a bonus and its magnitude. In column (5), the dependent variable is the log of total income in 2015 minus the log of total income in 2008. In all regressions, the coefficients on the noncompetitive tournament dummy and its interaction with overconfidence are not statistically significant and small in magnitude. Their inclusion does not change the lack of significance of the competitive dummy or the magnitude and significance of the interaction between competitive and overconfidence. In summary, we do not find that controlling for the noncompetitive dummy changes the conclusions reported in the paper.

C.5. Interaction of preferences for competition with other variables

In this subsection, we analyze whether the interaction between preferences for competition and other variables predicts the MBAs' income in 2015. Although there is a compelling argument for why preferences for competition interact with overconfidence. One might wonder whether this

Table IAXIV. Income in 2015 and preferences for competition or for high rewards

This table presents regressions of the log of total income in 2015 in column (1), the log of base salary in 2015 in column (2), a hurdle model of the likelihood of receiving a bonus in column (3) and of its magnitude (in logs) in column (4), and a regression of income growth, the log of total income in 2015 minus the log of total income in 2008, in column (5). Linear estimates are reported in columns (1), (2), (4), and (5). Marginal effects are reported in column (3). Standard errors are in parentheses. ***, **, and * indicate statistical significance at the 0.01, 0.05, and 0.10 level, respectively.

	Total income	*Base salary*	Bonus *Obtain*	Bonus *Size*	*Income Growth*
	(1)	(2)	(3)	(4)	(5)
Woman	−0.391***	−0.198**	−0.004	−1.022***	−0.265**
	(0.105)	(0.082)	(0.046)	(0.238)	(0.106)
Competitive	0.011	−0.023	0.020	0.055	−0.041
	(0.097)	(0.067)	(0.051)	(0.179)	(0.114)
Non-competitive tournament	0.137	0.112	−0.001	0.142	0.104
	(0.101)	(0.072)	(0.052)	(0.192)	(0.118)
Overconfidence	−0.004	−0.026	−0.030	0.119	−0.026
	(0.053)	(0.030)	(0.034)	(0.109)	(0.056)
Competitive × Overconfidence	−0.215**	−0.100*	−0.029	−0.513***	−0.212**
	(0.091)	(0.059)	(0.044)	(0.191)	(0.099)
Non-competitive tournament	−0.007	0.010	−0.056	0.187	−0.007
× Overconfidence	(0.100)	(0.068)	(0.048)	(0.207)	(0.105)
Obs.	250	250	250	218	250
F-test/χ^2 test	4.791	2.069	15.118	36.115	3.297
R^2	0.126	0.077			0.081

occurs for all determinants of tournament entry in the experiment. Hence, in Table IAXV, we rerun selected regressions from Table VIII, including these additional interactions. We concentrate on the dependent variables that exhibit the strongest interaction between preferences for competition and overconfidence: total income in columns (1) through (4) and the magnitude of the realized bonus in columns (5) through (8). In columns (1) and (5), we reproduce the regressions of VIII with the interaction between preferences for competition and overconfidence. In columns (2) and (6), instead of overconfidence, we interact preferences for competition with our measure of risk aversion (the standardized CRRA coefficient). In columns (3) and (7), we interact preferences for competition with standardized performance. Finally, in columns (4) and (8), we include all these interaction terms simultaneously.

We find that the interaction between preferences for competition and risk aversion is positive,

Table IAXV. Interaction of preferences for competition with risk aversion and performance

This table presents regressions of the log of total income in 2015 in columns (1) to (4) and hurdle models of the likelihood of receiving a bonus (not shown) and of its magnitude (in logs) in columns (5) to (8). Linear estimates are reported in all columns with standard errors in parentheses. ***, **, and * indicate statistical significance at the 0.01, 0.05, and 0.10 level, respectively.

	Total income				Bonus size			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Woman	-0.391^{***}	-0.366^{***}	-0.386^{***}	-0.372^{***}	-1.008^{***}	-0.954^{***}	-0.988^{***}	-0.975^{***}
	(0.106)	(0.105)	(0.108)	(0.102)	(0.240)	(0.241)	(0.247)	(0.236)
Competitive	0.055	0.042	0.056	0.069	0.089	0.107	0.107	0.117
	(0.089)	(0.091)	(0.091)	(0.090)	(0.170)	(0.172)	(0.172)	(0.171)
Overconfidence	0.011	-0.084^{*}	-0.084^{*}	-0.012	0.154	-0.022	-0.026	0.135
	(0.051)	(0.048)	(0.046)	(0.054)	(0.105)	(0.101)	(0.100)	(0.112)
Risk aversion	-0.099^{**}	-0.164^{***}	-0.105^{**}	-0.163^{***}	-0.109	-0.221^{**}	-0.120	-0.221^{**}
	(0.043)	(0.056)	(0.043)	(0.054)	(0.086)	(0.104)	(0.087)	(0.104)
Competitive ×	-0.219^{***}			-0.176^{*}	-0.425^{***}			-0.398^{**}
Overconfidence	(0.077)			(0.093)	(0.162)			(0.196)
Competitive ×		0.130		0.132		0.238		0.244
Risk aversion		(0.084)		(0.081)		(0.168)		(0.164)
Competitive ×			0.191^{**}	0.093			0.264	0.063
Performance			(0.090)	(0.106)			(0.181)	(0.217)
Obs.	250	250	250	250	218	218	218	218
F-test/χ^2 test	5.917	5.161	5.412	4.658	33.804	30.758	33.287	39.130
R^2	0.120	0.105	0.112	0.132				

suggesting that the negative association between risk aversion and income is weaker for competitive individuals. However, the coefficient on this interaction is never statistically significant. The interaction between preferences for competition and performance is positive and statistically significant for income when it is included alone. However, the coefficient on this interaction is much smaller and no longer statistically significant when the other interactions are included in the regression. Importantly, the interaction between preferences for competition and overconfidence is not affected much by the inclusion of these other interactions. Specifically, the magnitude of the coefficient is similar and remains statistically significant.

IAIV. Procedures for the initial survey and experiment

This section describes the procedures used to conduct the initial survey and the experiment. We concentrate on the parts of the survey and experiment relevant to the paper. Further details can be found in Reuben et al. (2008), including all survey questions and experimental instructions.

A. The initial survey

Participants completed the online survey in the fall of 2006. The deadline to complete the survey was the day participants took part in the experiment. Completing the survey was a requirement to pass one of the MBA core courses and took approximately one hour. The survey included questions on demographic characteristics and standard questionnaires of personality traits. We do not use the survey variables in the main body of the paper, but we do use them in the robustness checks. In Section IAV below, we describe the variables used in these checks.

B. The experiment

We ran the experiment in October 2006 in four sessions of around 140 participants. It lasted for about 90 minutes. Participation in the experiment was a requirement of one of the MBAs' core courses. The experiment was programmed and run using zTree (Fischbacher, 2007).

The experiment consisted of eight parts: three decision problems and five games. Participants played the eight parts in the following order: lottery with losses, asset market game, trust game, preferences for competition game, chocolate auction, social dilemma game, lottery without losses, and discount rate elicitation task. We gave the instructions for each part before the start of the respective part (the only exception being the instructions for the asset market game, which they received before their arrival). Importantly, participants received no information about the outcome of the games or lotteries during the experiment. Instead, they received feedback on their performance in specific games and on the behavior of other participants a few days later through an email.

Participants received a $20 show-up fee, which could be used to cover potential losses during the experiment. Also, we paid participants the amount they earned in one randomly chosen part (we did the randomization only among six parts since we always paid the lottery with losses and discount rate elicitation tasks). We paid participants who earned more than the show-up fee with a check delivered to their mailbox. Including the show-up fee, participants earned $99 on average (the standard deviation was $63).

In the main body of the paper, we describe the parts of the experiment used to measure preferences for competition. Below, we provide the instructions for these parts of the experiment. Moreover, in Section IAV, we describe the parts of the experiment used to measure the additional control variables utilized in the robustness checks.

B.1. Instructions for the sums tasks

This game is divided into 4 periods. At the beginning of the game, you will be divided into groups of four. The participants in your group will be the same throughout the 4 periods.

In each of the first 3 periods, you will be given a series of *addition tasks* (sums of four 2-digit numbers like the one below). You will have 150 seconds to answer as many questions as you want. The computer will record the number of sums that you answer correctly. You may use paper and pencil, but you *cannot* use a calculator. In each period, the rules for the payment are different and will be explained in detail before the start of the respective period.

One of the 4 periods will be randomly selected by the computer to determine your earnings for Game 3. In addition, after period 4, there will be a bonus section consisting of four questions. Any money earned in the bonus section will be added to this experiment's earnings.

B.2. Instructions for the piece-rate period

In this period, you will be paid $4 for each correct answer you give.

Example: If you answer 6 questions correctly, your earnings for period 1 equal $24. Remember, you can write down the numbers on a piece of paper, but you *cannot* use a calculator.

B.3. Instructions for the tournament period

In this period, you will compete against the other *three participants* in your group. Your payment is contingent on you having the highest number of correct answers. You will be paid $16 for each correct answer if you have the *highest* number of correct answers in your group. If you do not have the highest number of correct answers, you will earn $0 in this period. If there are two or more group members tied in first place, one of them will be randomly selected to be paid $16 for each correct answer (the others are paid $0). Note that all group members will face the same difficulty. That is, everyone will face the same sequence of numbers.

Example: Suppose that the other three participants in your group answer 5, 9, and 12 questions correctly. If you answer 11 questions correctly, your earnings in this period would equal $0. If you answer 13 questions correctly, your earnings in this period would equal $208. Remember, you can write down the numbers on a piece of paper, but you *cannot* use a calculator.

B.4. Instructions for the choice period

In this period, you will replay the same game, but you choose the rule according to which you will be paid. You can be paid with Rule 4 or with Rule 16:

Rule 4: If you choose this rule, you will be paid $4 for each correct answer regardless of what others do.

Rule 16: If you choose this rule, you will be paid according to your performance relative to the performance of the other three group members. You will earn $16 for each correct answer if you have more correct answers than the other group members had in period 2. If you do not have more correct answers than the other group members had, you will earn $0 in this period. If you tie in first place, a random draw will determine whether you are paid $16 for each correct answer or $0.

Remember, you can write down the numbers on a piece of paper, but you *cannot* use a calculator.

B.5. Instructions for the uncompetitive choice period

In this period, you do not have to repeat the addition task, but you have the choice to be paid *again* for your period 1 performance in two ways. You can choose to be paid according to Rule 4 or Rule 16.

Rule 4: If you choose this rule, you will be paid $4 for each question answered correctly in period 1 regardless of what others did.

Rule 16: If you choose this rule, you will be paid $16 for each correct answer in period 1 if you have more correct answers than the other three group members had in period 1. If you did not have more correct answers than the other group members had, you will earn $0 in this period. If you tie in first place, a random draw will determine whether you are paid $16 for each correct answer or $0.

Recall that in period 1, you correctly answered *XX questions*. Note that this choice determines your period 4 earnings; it does not affect your earnings from period 1.

B.6. Instructions to elicit the participants' expected rank in each period

In this screen, we would like you to estimate your performance relative to that of the other three players. For each of the first three periods, indicate whether you think you ranked first, second, third, or fourth. You will receive $2 for every period in which you correctly estimate your rank. In case of a tie, you will receive the $2 if there is a way of resolving the tie that makes your estimate correct.

Example: Suppose that in period 1 you had 8 correct answers and the other three group members had 6, 8, and 11 correct answers. You will receive $2 if you guess that your rank is second or third in period 1.

IAV. Description of additional control variables

This section describes the additional control variables used in the robustness checks. We divide them depending on the data source: administrative data from the University of Chicago, the initial survey, or the experiment.

A. Administrative data

In addition to gender, the business school supplied us with the following variables:

- Age (in months).
- Race, which we used to construct a dummy variable indicating non-white individuals.
- Visa status, which we used to construct a dummy variable indicating whether an individual is a US resident (citizen or legal resident).
- Marital status, which we used to construct a dummy variable indicating a married individual.
- GMAT percentile scores. Both the aggregate score and the score of each of the three components: quantitative, verbal, and analytic.
- GPA at graduation.
- The number of dollars students donated to their class gift to the University of Chicago.

Note that all these variables, except for GPA and donations to the university, were collected in 2006, before the students started their MBA. We collected the last two variables in 2008 at graduation.

B. Initial survey

We use the following variables from the initial survey in the robustness checks.

- Religiosity, which we measured with the yes/no question: "Are you religious now?"

- A self-reported measure of the participants' general attitude toward risk, which has been shown to correlate with incentivized measures of risk aversion and is commonly used in the literature (Falk et al., 2018). It consists of the question: "Are you generally a person who is fully prepared to take risks or do you try to avoid taking risks? Please select a number between 0 and 10 where 0 means unwilling to take risks and 10 means fully prepared to take risks." For this variable to measure risk aversion, we reverse-coded it so that higher numbers imply more aversion to risk.
- Another self-reported measure of the participants' attitudes toward risk was elicited in the monetary domain. Specifically, we asked participants to indicate: "What is the maximum price you are willing to pay for a ticket in a lottery that pays you \$5K with 50% probability and nothing with 50% probability?" For this variable to measure risk aversion, we use \$2.5K minus their answer to the question so that higher values imply more aversion to risk.
- We elicited the participants estimated academic performance by asking them: "In your future exams at the University of Chicago, in which decile of the GPA distribution do you expect yourself to be?" We then used their answer to this question minus their actual GPA decile at graduation to create the non-incentivized survey measure of overconfidence.
- We measured the participants' tendency to suppress intuitive responses using the Cognitive Reflection Test or CRT (Frederick, 2005). We simplified the original test to four questions: (i) A bat and a ball cost \$1.10 in total. The bat costs \$1.00 more than the ball. How much does the ball cost? (ii) If you flipped a fair coin 3 times, what is the probability that it would land "heads" at least once? (iii) If it takes 5 machines 5 minutes to make 5 widgets, how long would it take 100 machines to make 100 widgets? (iv) Two cars are on a collision course, traveling toward each other in the same lane. Car A is traveling 70 miles an hour. Car B is traveling 80 miles an hour. How far apart are the cars one minute before they collide? The CRT score consists of the number of correct answers.
- To measure the participants' ability to detect emotions (a key component of emotional intelligence), we use the "reading the mind in the eyes" test or RMET (Baron-Cohen et al., 2001). It consists of correctly recognizing the emotions of various individuals by looking at pictures of their eyes. The RMET score consists of the fraction of correct answers.

C. Experiment

From the experiment, we use the following measures of important individual characteristics.

C.1. Discount rate

To measure time preferences, we gave participants a series of choices of the following form: receive x dollars today or receive $(1 + y)x$ dollars in two weeks, where x equaled their earnings in the experiment. Each subject answered thirteen such questions where y varied from 0 to 0.12 in steps of 0.01. After that, one of the questions was randomly selected and paid. We always paid participants by dropping a check into their mail folder during a day in which they had to attend class.

C.2. Trust and reciprocity

We measure the participants' propensity to trust and reciprocate by having them play a trust game (Berg et al., 1995). In the game, a first-mover is endowed with $50 and decides how much to send to a second-mover (in multiples of $5). Any amount sent is multiplied by three. The second mover then decides how much to return to the first mover.

Each participant played two trust games. First, they played as the first mover and then as the second mover. Participants made their second-mover decision using the strategy method. They indicated how much to return for each possible sent amount without knowing how much the first mover actually sent. They received no feedback between decisions and knew they were not playing with the same participant. We use the fraction of the $50 sent as first movers as the participants' measure of trust and the fraction they returned conditional on receiving $150 as their measure of reciprocity.

C.3. Cooperation

To measure their willingness to cooperate, participants played a variation of the design used by Fischbacher et al. (2001). Specifically, participants were randomly assigned to groups of eight, given an endowment of $50, and asked to make two contribution decisions to a linear public good game: an "unconditional" and a "conditional" decision. For their unconditional decision, each participant i indicated whether they are willing to contribute $c_i \in \{0, 50\}$ to the public good. For their conditional decision, each participant i indicated whether they are willing to contribute $c_i(x) \in \{0, 50\}$ given that $x \in \{0, 1, 2, 3, 4, 5, 6, 7\}$ other group members contribute. To determine the final contributions to the public good, seven unconditional decisions were selected at random and were used to determine the conditional decision of the remaining group member. Participant i's earnings equaled $50 - c_i + 0.3 \times \sum_j c_j$.

We use the unconditional contribution as a participant's willingness to cooperate.