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OVERCONFIDENCE AND PREFERENCES FOR COMPETITION

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ABSTRACT

We study whether and when preferences for competition are a positive economic trait among high-earners and to what extent 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 non-overconfident individuals. Preferences for competition correlate with income only at graduation when bonuses are guaranteed and not a function of performance. Overconfident, competition loving MBAs have 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 compensations, which is even larger than in regular jobs (Bertrand and Hallock (2001), Kulich et al. (2011), Blau and Kahn (2017)). One possible explanation for this gap is the fact, documented by Niederle and Vesterlund (2007), that women shy away from competitive tournaments.[1] This hypothesis is strengthened by recent papers that have used 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)). All these studies find that preferences for competition boost positive economic outcomes.[2] The cumulative evidence is sufficiently strong that Balafoutas et al. (2018) have proposed using priming to eliminate this gender difference in the willingness to compete and generate more gender balanced outcomes in labor markets.

In Niederle and Vesterlund (2007)'s original lab experiment, however, preferences for competition were not necessarily conducive to better economic outcomes. A risk-neutral individual is better off choosing the tournament in the lab only if she belongs to the top 37% of the skill distribution. In fact, 53% of the men chose to compete, even if 16% earned less because of that choice. Thus, liking competition is not an unequivocally good trait: overconfident people who like to compete when they should not, end up earning less. The subsequent literature has yet to investigate whether this result carries over to the field, particularly in jobs where pay is strongly linked to performance.

In this paper, we investigate whether and when preferences for competition are a positive economic trait among high-earners and to what extent 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

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

[2]Buser et al. (2014)'s analysis 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 playing professional sports. Lastly, Zhang (2019) finds that willingness to compete predicts whether middle school students in rural China take a highly demanding high school entrance exam.

pay-per-performance. We have data on earnings at two junctures: at graduation, when earnings are unrelated to performance on the job, and seven years later, when earnings are based on performance on the job.[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 might change over time.

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 business school, eighteen months before the first job decision. To measure 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 zero otherwise). The 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 preferences for competition and overconfidence.

We start by studying the relationship between preferences for competition and income

[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.

[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 have consistently found 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)).

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), and gender differences in preferences for competition account 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, and so 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 that employers might have offered higher salaries in expectation of higher performance.

In our data, there are two industries where salaries are higher, there is greater pay-performance sensitivity, 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. competition-loving individuals are 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. At this point, we do not find that preferences for competition alone predict either income or industry choice. Instead, we find that risk aversion and overconfidence negatively correlate with income. By contrast, we observe a dramatic

[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. Thus, it accounts for variance in earnings and the gender gap that would otherwise remain unexplained.

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 us explain any fraction of the gender gap.

These divergent trends over time raise three questions. Why do preferences for competition predict income at graduation but not seven years later? Why do other traits (overconfidence and risk aversion) become significant? What drives the opening of the gender gap during the seven years that follows graduation?

To answer these questions, we build on the insight of the original Niederle and Vesterlund (2007) experiment that participants only sometimes benefit from competing. Specifically, participants who mistakenly believe they will outperform others and choose the tournament will 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 is mainly concentrated 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 firmly based on performance, as they are in our sample seven years after graduation, employees who underperform will experience lower growth in income, be weeded out from high-reward industries, and experience more frequent career interruptions (as a measure of potential firings). Overconfident MBAs, particularly those who love competition, are likely to underperform. Thus, we should expect the interaction between overconfidence and preferences for competition to be significantly associated with lower income growth after graduation, a higher probability of exiting the high-reward industry, and a higher probability of career interruptions longer than six months. We find evidence for all these three 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. They cannot explain directly (the effect is statistically nil), but they cannot even explain it interacted with overconfidence since men have the largest combination of high overconfidence and preferences for competition, and this interaction has a negative effect on 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 where income is based on performance to one where 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 appear when the compensation is not performance-based.

The closest paper to ours is a contemporaneous paper 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, this paper 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, whose mean gross income is only $35k (the mean income in our sample is more than five times this amount at graduation and almost ten times greater seven years later). Our paper is the only one that studies high earners and income at two points in time. Finally, our paper is the only one that tests an important prediction of Niederle and Vesterlund (2007) original lab experiment: 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

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

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 of 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. Finally, we discuss potential mechanisms for our findings in Section VI and conclude in Section VII.

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 of 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 the 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 business school. Participants completed the survey online before they took part in the experiment. The survey included questions on demographic characteristics and standard questionnaires of personality traits.

The experiment consisted of eight distinct parts. Participants were given the 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 Online Appendix, we provide a detailed description of the procedures used to conduct the survey and experiment and the instructions for the tasks used to measure preferences for competition (the 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. Subsequently, they performed the task again under the payment scheme of their choice. Their payment-scheme choice serves as the basis for 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 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.[7] 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 piece rate, participants earned \$4 for every correct answer. Under tournament, participants earned \$16 for every correct answer if they had the highest number of correct answers in their group (ties were broken randomly) and earned \$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.

[7]To avoid group composition effects (e.g., see 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 opted for random assignment to groups without informing the participants with whom they are matched. We ran sessions of over 150 participants; hence, participants couldn't 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).

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 piece rate earned \$4 per correct answer. Participants who chose tournament, earned \$16 per correct answer if they had more correct answers than their other group members had 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.[8]

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

To measure individual performance, we compute the participants' average rank in the first and second periods. For this variable to not depend on the specific group matching in the experiment, we used the number of sums solved by the participants and simulated 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.[9]

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[8]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, the 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 *non-competitive tournament* is a dummy variable equal to one when an individual chooses tournament pay in this period.

[9]Many studies in the literature use the number of correct answers as the measure of performance.

After the fourth period, we elicited the 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 1^{st} and 4^{th} and received \$2 for each correct guess.[10] 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 with the gender variable. The business school's career services office provided us with information regarding the job participants accepted upon graduation. The 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 it with the respective employers to ensure its accuracy. The information included 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 where offers include an upper and lower range for a bonus, students are required to report the minimum (guaranteed) bonus. Based on this information, we calculated the participants' total earnings in their first year after graduation. We also received self-reported information from the career services office about the participants, including whether they obtained competing job offers. Because all these income components are set in advance, and bonuses are based on the minimum guaranteed bonus, our measure of income in 2008 can be based only on expected performance, not realized performance.

We opt for the 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.

[10] In 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 the 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. Out 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. Throughout the paper, we concentrate on these participants. However, it is important to understand whether this sample differs systematically from the rest of the cohort. For this reason, in the Online 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.[11] By and large, we do not find differences between these two populations (see Table AI in the Online 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, $p > 0.388$).[12] Similarly, to understand selection into the sample who responded to the 2015 follow-up survey, in Table AII in the Online Appendix, we compare the characteristics of the 263 respondents and the 146 non-

[11] 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 they did not have a job offer.

[12] 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, $p > 0.704$).

respondents who had consented to the analysis of their data. The results show that 2015 respondents are positively selected on measures of career success. Non-respondents are more likely to have lower salaries in 2008, be women, and be overconfident, all of which correlate negatively with income in 2015. We will discuss the potential implications of this selection on our results later.

Next, we 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 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)). Next, we focus on differences in preferences for competition between male and female MBAs.

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, on its own, the higher incidence of men choosing the tournament is not enough to conclude that men like to compete more. In particular, 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 vs. 0.16 by women). Combined 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 answer this question, we follow Buser et al. (2014) and run a series of probit regressions with the participants' tournament choice as the dependent variable. We report the resulting marginal effects in Table II. In column

Table I

Summary statistics by gender

Means, standard deviations, and the number of observations for variables used in the paper. The rightmost column displays p-values from tests of 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
Non-competitive 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

Table II

Determinants of willingness to compete

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

	(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

(1), the only independent variable is the participants' gender. Without any controls, the gender gap in choosing the tournament equals 27%. In column (2), we control for the participants' performance, which reduces the gender gap in choosing the tournament to 22%. In column (3), we further control for the 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 (column (3)). The gender dummy's coefficient, once we control for performance, beliefs, and risk preferences, can be interpreted as a gender difference in preferences for competition.[13]

[13]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 the overestimation of gender differences (Gillen et al. (2019), van Veldhuizen (2022)). In the Online Appendix, we run a series of robustness checks to test whether this result is susceptible to this problem (see Tables AIII to AV). We do not find evidence that it is.

B. Income in 2008

The business school's career office collects data on the base salary and bonuses of all the 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 the base salary and bonus pay. We group the various bonuses into two components: one-off bonuses (relocation, tuition, sign-on, and retention at year-end) and the rest, which are guaranteed bonuses related to the performance of their new hires (stock options, profit sharing, guaranteed performance, and other). We call this latter component 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 are primarily concentrated in the bonus, not the base salary. For example, men's average bonus pay is 80% higher than women's. The difference is even starker in the guaranteed performance bonus component, where men's bonus pay is 404% higher than women's.[14]

The large gender gap in total income is partly due to three male outliers, with salaries above \$1M. If we ignore those, the average male total income drops to \$170K, the gender gap is reduced to 14%, and the average overall bonus pay for men becomes 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 the 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 will refer to it as 2015 income, even if it is technically the sum of the 2015

[14]One conjecture 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 is that men overstate the bonus rather than follow the instructions of the career services office to report the minimum amount in the range. We discuss this hypothesis later.

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 concentrated in the bonuses, where men's are 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 used to classify them into three broad industry categories. Specifically, we used 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 perception is that salaries and career paths in these industries differ, with finance and consulting offering higher pay-for-performance and, more generally, 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 grows 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 in Table III suggests that these are up-or-out industries. Specifically, it shows that MBAs leave consulting and finance to other industries, but 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. By contrast, only 13% of those who start working in other industries move to either consulting or finance.

In summary, this section shows that our lab experiment replicates the results of

Table III

Industry characteristics

Panel A shows the mean total income earned by MBAs in 2008 and 2015, depending on the industry they are working 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 of them working 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

Niederle and Vesterlund (2007), namely that women shy away from competition. Moreover, our sample exhibits a gender gap in income in 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 the participants' earnings that does not depend on the matching realized in the experiment. Specifically, we take the distribution of solved sums and simulate one million matches to obtain the expected experimental earnings of each participant if their payment was 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 then control for performance in column (2). Once we control for performance, which is highly statistically significant, the coefficient of 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, being overconfident has a significantly negative effect on earnings. By contrast, neither gender nor risk aversion are significant determinants of experimental earnings. Adding these explanatory variables does not reduce the coefficient of 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 competitive and overconfidence. We observe that the coefficient of 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. Hence, it is evident from the experiment that the combination of preferences for competition and overconfidence has negative effects on earnings.[15]

[15]In the experiment, the average competition-averse participant underestimates their performance in absolute terms. Underestimating one's performance in absolute but not in relative terms is commonly observed in experimental tasks that are considered difficult (see Moore and Healy (2008)). Thus, a bit

Table IV

Determinants of experimental earnings in the lab

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

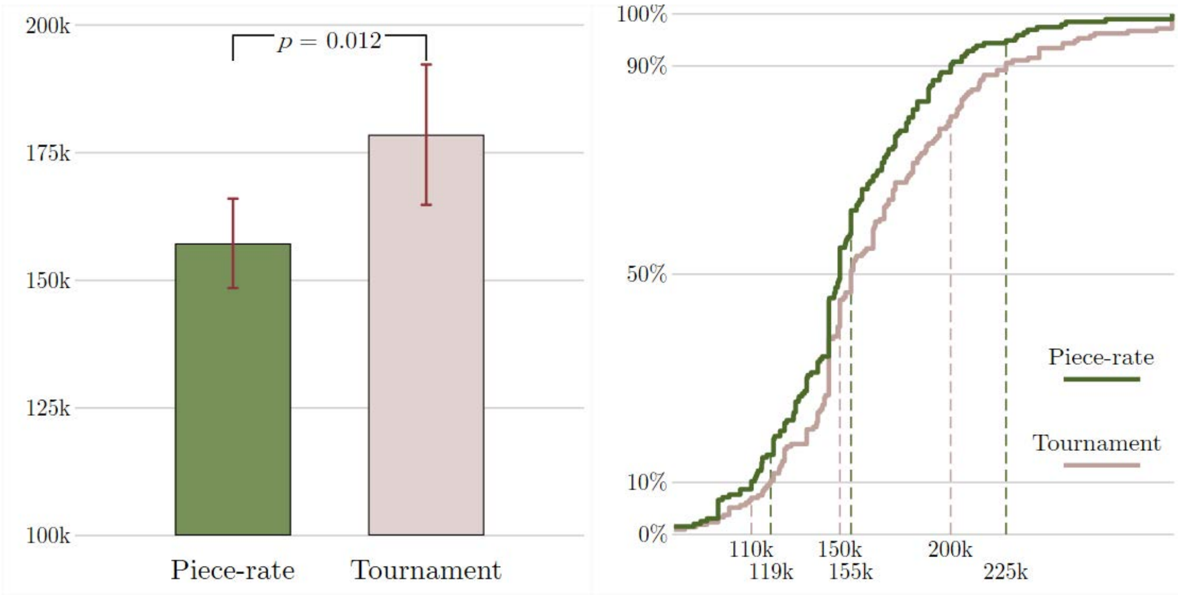
	(1)	(2)	(3)	(4)
Competitive	0.396***	0.125**	0.191***	0.218***
	(0.057)	(0.049)	(0.051)	(0.048)
Performance		0.405***	0.355***	0.323***
		(0.026)	(0.028)	(0.028)
Woman			−0.021	−0.017
			(0.050)	(0.045)
Risk aversion			0.020	0.017
			(0.022)	(0.020)
Overconfidence			−0.091***	0.061***
			(0.026)	(0.017)
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

IV. Preferences for competition and income in 2008

We now move to our first income data. Figure 1A 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 post-MBA job. On average, participants who chose the tournament earn \$21K more than participants who chose piece-rate (t-test, $p = 0.012$). The difference in earnings is larger for top earners (see Figure 1B).

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

of overconfidence is good for competition-averse participants because it corrects a systematic bias. For competition-loving participants, overconfidence has a clear negative effect.



Panel A Panel B

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.

aversion, and performance in the adding task.

We find that competition-loving MBAs earn 7.9 log points more at graduation than their competition-disliking 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. However, in our case, 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 to wage compression at this stage of an MBA's career and that most companies have predetermined wages for newly hired MBAs, we find this result 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

Table V

Determinants of income in 2008

Regressions of the log of total income in 2008 in column (1) and the log of base salary in 2008 in column (2). Hurdle model of the likelihood of obtaining a bonus in column (3) and its size in column (4). 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 in columns (1), (2), (4), (6), and (8). Marginal effects 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 in parenthesis. ***, **, and * indicate statistical significance at 0.01, 0.05, and 0.10.

	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						

variable, the coefficient for 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 non-negligible effect.[16]

To better understand the relationship between income and preferences for competition, in columns (2) to (4), we separate the base salary and the bonuses.[17] 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 a larger base pay. Since not all MBAs receive a bonus, and we are estimating the regressions in logs, we opted for a two-step hurdle model to estimate first the impact of the independent variables 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 the competition-loving and gender are correlated with the size of the bonuses. competition-loving MBAs receive $8K (15.8 log points) more in 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. competition-loving MBAs obtain a bonus that is 57.1 log points higher (≈$13K) than the rest. By contrast, preferences for competition do not seem to affect the amount of

[16]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 should point out 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)).

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

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. However, this is not true: one-off bonuses are \$25K at the 25th percentile and \$55K at the 75th percentile, an interquartile range of \$30K, which is similar to that of the guaranteed performance bonuses (\$37K).

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

Some industries tend to pay MBAs significantly more (Oyer (2008)). Thus, income can 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 check how the results change if we control for the industry chosen by the MBAs at graduation. We do this 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 of both the preferences for competition and gender dummies are only slightly smaller. Thus, industry sorting does not seem to be the primary driver of our results.[18]

So far, we have not studied 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 this in Table VI by adding the interaction of these two variables to the specifications used in Table V. The coefficient of interaction between overconfidence and preferences for competition is negative in all

[18]In the Online Appendix, we report the results of two other robustness checks. In Table AVI, 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 AVII, we repeat our basic specification adding a large set of individual controls to the regression (following Bertrand et al. (2010)). In both cases, we find very similar results.

but one specification. However, it is not statistically or economically significant in any regressions. 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 of the other variables. These results are consistent with income not being closely tied to performance at this point in the MBAs' careers.

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; they prefer high rewards. To address this possibility, we use a clever feature of the experimental design of Niederle and Vesterlund (2007): 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 8). 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 determined by preferences for non-linear payoffs that reward high performers. In Table AVIII in the Online Appendix, we replicate the analysis in Table V, 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 competitive 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 not different from zero. By contrast, the coefficient of competitive remains substantially unchanged in all specifications. These results provide compelling evidence that the association between tournament and income is indeed driven by the 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

Table VI

Interaction between preferences for competition and overconfidence in 2008

Regressions of the log of total income in 2008 in column (1) and the log of base salary in 2008 in column (2). Hurdle model of the likelihood of obtaining a bonus in column (3) and its size in column (4). 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 in columns (1), (2), (4), (6), and (8). Marginal effects 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 in parenthesis. ***, **, and * indicate statistical significance at 0.01, 0.05, and 0.10.

	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***	−0.074	−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						

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 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.[19] This interpretation would imply that our participants disregarded the instructions from the career services office, which explicitly requested to report the minimum of a range when offered a range in the bonus. Could this be an explanation for our results?

Note that we already included 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 experiment. 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.[20] The answers, collected in private, were never communicated to others. Afterward, students were 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.[21] In Table AX in the Online Appendix,

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

[20]If the students' estimate was within one addition of their actual performance, they earned $50 and otherwise $0.

[21]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

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 used 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 of 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 of risk aversion is larger and has a significantly negative impact on income. The coefficient of overconfidence is also negative and larger in magnitude, reaching statistical significance at the 10% level.

In line with previous research (Bertrand et al. (2010)), the gender gap is much larger several years after graduation. The coefficient of 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 re-estimate the same specification with the log of the base salary as

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. Unlike for 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

Regressions of the log of total income in 2015 in column (1) and the log of base salary in 2015 in column (2). Hurdle model of the likelihood of obtaining a bonus in column (3) and its size (in logs) in column (4). Linear estimates in columns (1), (2), and (4). Marginal effects 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 in parenthesis. ***, **, and * indicate statistical significance at 0.01, 0.05, and 0.10.

	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		

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 2015 is that coefficient of overconfidence 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 of the gender dummy, but it does not affect the coefficients of 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 visualizes 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 seen in the figure, the effect

Table VIII

Interaction between preferences for competition and overconfidence in 2015

Regressions of the log of total income in 2015 in column (1) and the log of base salary in 2015 in column (2). Hurdle model of the likelihood of obtaining a bonus in column (3) and its size (in logs) in column (4). Linear estimates in columns (1), (2), and (4). Marginal effects 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 in parenthesis. ***, **, and * indicate statistical significance at 0.01, 0.05, and 0.10.

	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		

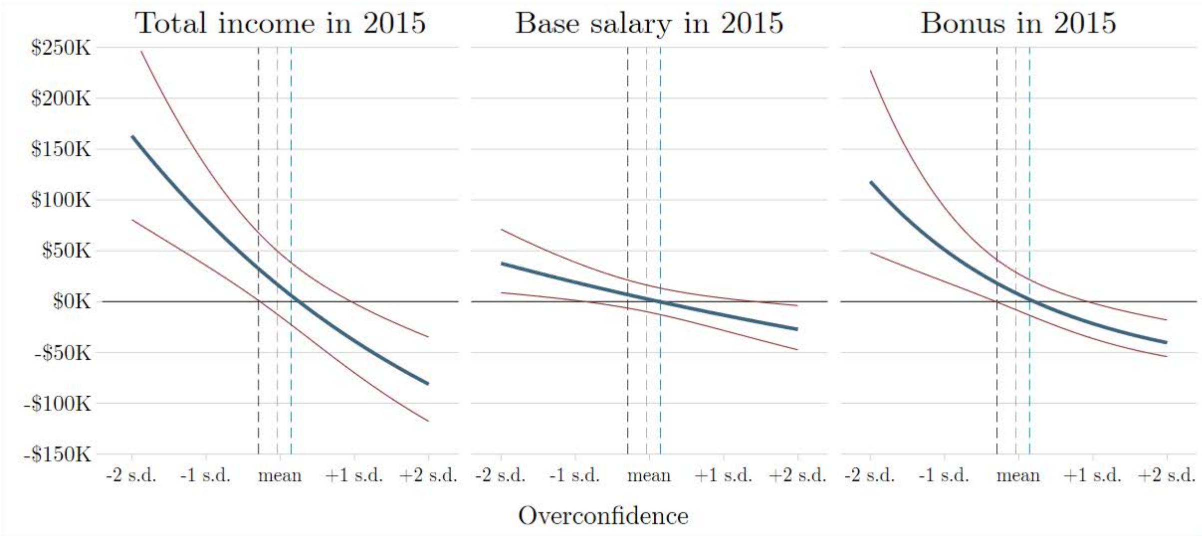


Figure 2. Estimated marginal effect of preferences for competition on income in 2015 at different levels of overconfidence. The figure is based on the regressions in Panel A of Table VIII. Blue lines correspond to the estimated marginal effect, and red lines constitute 90 percent confidence intervals. The light blue dotted line corresponds to the average overconfidence of men, the red dotted 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).

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 component most firmly tied to individual performance, namely the bonus (see also Figure 2).[22]

[22] The Online 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 AXII), adding a large set of individual controls (Table AXIII), and considering the participants' "preference for high rewards" (Table AXIV). In Table AXV, we run the same regressions as in Table VIII, including the interaction of preferences for competition with 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.

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 re-estimate 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 where preferences for competition have an effect in 2008.

In columns (1) and (2), the coefficients for preferences for competition are about the same magnitude as in the entire sample but are not statistically different from zero. Thus, in the 2015 sample, we certainly have a power issue. Still, this is not the only reason the coefficient of 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 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 are correlated 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 Online Appendix, we use a Heckman selection model to evaluate the robustness of our results.[23]

[23]More specifically, we use independent measures of the MBAs' tendency to answer University surveys

Table IX

Determinants of income in 2008 using the 2015 sample

Regressions of the log of total income in 2008 in columns (1) and (2). 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 in parenthesis. ***, **, and * indicate statistical significance at 0.01, 0.05, and 0.10.

	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						

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 the selection in the 2015 sample. In all regressions in Table IX, the coefficient of 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 of preferences for competition remains insignificant in all specifications while the coefficients of 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.[24]

The main difference between the 2008 and the 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 the participants who choose to compete are guaranteed the expected earnings of the average participant that competes, and all the 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

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 AXI and the corresponding description in the Online Appendix for the details.

[24] 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 of the gender dummy drops by a third in absolute value (but remains negative and statistically significant).

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 confirm this hypothesis.

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 this 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 per 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

Table X

Determinants of working in a high-reward industry

Regressions of working in either finance or consulting. Marginal effects from probit regressions. 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 in parenthesis. ***, **, and * indicate statistical significance at 0.01, 0.05, and 0.10.

	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	14.08	14.274	7.872	11.755

overconfidence in 2008, but in 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, 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

Table XI

Determinants of income growth between 2008 and 2015

Regressions of income growth, the log of total income in 2015 minus the log of total income in 2008. Linear estimates. 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 in parenthesis. ***, **, and * indicate statistical significance at 0.01, 0.05, and 0.10.

	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

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 (≈\$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. Namely, 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 of career success.[25] 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 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 accounting for these proxies of career paths helps explain the effect of the interaction of preferences for competition and overconfidence. We rerun the regression of total income reported in Table VIII, including, first separately and then together, 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 Tables 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 are positively associated.

[25]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 of competition and overconfidence

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 in columns (1) through (6). Marginal effects 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 in parenthesis. ***, **, and * indicate statistical significance at 0.01, 0.05, and 0.10.

	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)

Regressions of the log of total income in 2015 in all columns. Linear estimates. 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 in parenthesis. ***, **, and * indicate statistical significance at 0.01, 0.05, and 0.10.

	(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 $\times$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

Although all the measures of career paths correlate significantly with income, inserting them in the regression impacts the coefficients of 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 of 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 6 log points more. Overall, the coefficient of the interaction between preferences for competition and overconfidence goes from 21.9 log points in column (1) of Table VIII to 11.7 in column

Table XIV

Career paths and the effect of preferences for competition and overconfidence on income in 2015 (with industry fixed effects)

Regressions of the log of total income in 2015 in all columns. Linear estimates. 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 in parenthesis. All regressions include industry fixed effects. ***, **, and * indicate statistical significance at 0.01, 0.05, and 0.10.

	(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

(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. Conclusions

We find that preferences for competition have a long-term effect on the income of highly-paid business professionals whose compensation is highly dependent 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. On the contrary, 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 different 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, even though 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.[26]

These findings suggest caution with policies aiming to eliminate gender pay gaps by teaching 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 perspective, teaching men to be less overconfident could be more fruitful.

Our analysis is conducted on a sample of high-earning professionals whose income

[26]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.

is very 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 the performance on the job. Future research can shed more light by directly measuring job performance and how it relates to preferences for competition and overconfidence.

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