Measuring preferences for competition

LINA LOZANO

New York University Abu Dhabi, Center for Behavioral Institutional Design, e-mail: lina.lozano@nyu.edu

ERNESTO REUBEN

New York University Abu Dhabi, Center for Behavioral Institutional Design, Luxembourg Institute of Socio-Economic Research, e-mail: ereuben@nyu.edu

ABSTRACT

Individuals' willingness to compete is a key predictor of their educational and labor market outcomes. However, the factors underlying individuals' decisions to compete are still not fully understood. Recent research suggests that an important determinant of these decisions is simply how much individuals enjoy or dislike performing in a competitive environment. In other words, their preferences for competition. In this paper, we present an experiment designed to precisely measure individuals' preferences for competition. Our experiment has three distinct features. First, unlike previous work, competition-entry decisions are unaffected by risk preferences. Second, we use an intuitive and incentive-compatible method to elicit individuals' belief of winning. Third, we collect numerous decisions per individual, enabling us to estimate the monetary value of their preferences for competition, evaluate the consistency of their choices with expected utility maximization, and observe whether they exhibit a stable inclination or disinclination to compete. We find strong evidence that many individuals are willing to give up a sizable fraction of their expected earnings to either compete or refrain from competing. In addition, we find that individuals' decisions to compete are highly consistent with expected utility maximization, and most individuals are either persistently competition loving or persistently competition averse. We also find that preferences for competition depend on the number of competitors but not on gender.

This version: March 2023

ACKNOWLEDGEMENTS

We gratefully acknowledge financial support from Tamkeen under the NYU Abu Dhabi Research Institute Award CG005.

جامعة نيويورك أبوظبي

NYU | ABU DHABI

مركز التصميم السلوكي المؤسساتي

CENTER FOR BEHAVIORAL INSTITUTIONAL DESIGN

1 Introduction

In recent decades, economists have started to pay attention to non-cognitive factors as important determinants of economic behavior. For instance, Heckman et al. (2019) conclude that factors such as psychological traits and preferences explain important life outcomes, like wages and health. One such trait is preferences for competition. People face competition in many areas, such as the workplace or the educational system. Therefore, it is understandable that several studies have found that preferences for competition, as measured in laboratory experiments, predict important labor market and educational outcomes (e.g., Buser et al., 2014; Berge et al., 2015; Buser et al., 2017b; Reuben et al., 2017; Kamas and Preston, 2018; Reuben et al., 2019; Zhang, 2019; Buser et al., 2020, 2022; Dariel and Nikiforakis, 2022; for a review see Lozano et al., 2023).

Since the seminal paper by Niederle and Vesterlund (2007), many experimental studies have documented individual heterogeneity in the decision to compete (for reviews see, e.g., Niederle, 2017; Dariel et al., 2017). However, it is yet unclear what underlying factors drive competitive behavior (Gillen et al., 2019; Buser et al., 2020; van Veldhuizen, 2022). Is it due to individual differences in the ability to perform, beliefs about relative performance, and risk attitudes, or is it due to individual differences in preferences for competition? Given the importance of competition in determining economic outcomes, it is important to uncover whether decisions to engage in competitive behavior are influenced by a desire or dislike to perform in competitive environments.

Typically, preferences for competition are measured by asking participants in an experiment to choose how they wish to be paid for performing an adding task. Participants are given two options, which we call *individual pay* and *competitive pay*. Under individual pay, participants are paid a fixed amount per correct answer. Under competitive pay, they are paid a larger amount per correct answer but only if they have the highest performance in a randomly selected group (for details, see Niederle and Vesterlund, 2007). Often, preferences for competition are identified as the residual of regressing the payment choice on measures of other determinants of the decision to compete, namely, risk preferences, beliefs, and performance (e.g., Buser et al., 2014, 2017b; Reuben et al., 2017; Gillen et al., 2019; Buser et al., 2020; van Veldhuizen, 2022). We advance this experimental design by measuring preferences for competition in a setting that rules out risk preferences by design and elicits beliefs more precisely, which allows us to quantify the strength of individuals' preferences for competition. In addition, we collect multiple decisions per individual, which helps us evaluate the impact of decision errors.

To remove the effect of risk preferences on the decision to compete, we adjust the options of the payment choice. As in Niederle and Vesterlund (2007), participants who choose competitive pay earn a large amount per correct answer if they are the best performer in their group and a low amount otherwise. Unlike the traditional design, in our experiment, participants who choose individual pay take part in a lottery. If they win the lottery, participants earn the same large amount per correct answer as those who choose to compete and win and the same low amount otherwise. By using identical outcomes for both payment options, we ensure that risk preferences do not affect the participants' choices. This feature removes the need to statistically control for risk preferences and allows us to measure preferences for competition without making assumptions about the correlation between these two traits.

A crucial variable to identify preferences for competition is the participants' belief in their relative performance and, more precisely, their belief that they will be the best performer in their group. To measure this belief accurately, we incentivize the belief elicitation using a binarized scoring rule (Hossain and Okui, 2013). The advantage of this method is that it is unconfounded by varying levels of risk preferences and has been shown to outperform other belief elicitation methods (e.g., see Trautmann and van de Kuilen, 2015). In addition, we reduce noise in the elicitation of beliefs in two ways. First, we implement an interactive graphical interface that automatically calculates the applicable incentives (see, Danz et al., 2022). Second, we help participants calculate how their expected percentile ranking in the performance distribution translates into the probability of being the best performer in a randomly-formed group.

Another feature of our experimental design is that participants choose between competitive and individual pay using a multiple price list (MPL), where the probability of winning the lottery in individual pay gradually increases. For a given belief of being their group's winner, the point where participants switch from competitive to individual pay allows us to calculate the precise monetary amount participants are willing to pay to avoid or engage in competition. For instance, competition-neutral participants will switch from competitive pay to individual pay as soon as the probability of winning the lottery exceeds their expected probability of winning the competition. Participants who switch before this point accept a lower expected utility to avoid competition, which makes them competition averse. Analogously, participants who switch after this point accept a lower expected utility to keep competing, making them competition loving. In addition, the pattern of choices in the MPL allows us to identify whether a participant's competition-entry choices are consistent with expected utility maximization.

A common drawback of most studies that measure preferences for competition is that they rely on one competition-entry decision. Therefore, they do not observe how noisy individuals' decisions are. In our experiment, we elicit choices in five different settings, where each setting implies an MPL with ten different choices between competitive and individual pay. Thus, we have much more data to determine the role of decision error.

Finally, while the literature studying preferences for competition has increased considerably, there is yet little knowledge of how these preferences depend on the degree of competition individuals face. We contribute to this question by studying the impact of group size on preferences for competition by implementing competition in groups of three and six.

We find strong evidence that most individuals have preferences for competition. Most participants, 75%, are either reliably competition loving or competition averse across settings and their decisions within settings are highly consistent with expected utility maximization. Specifically, 45% of participants in our sample consistently switch from competitive to individual pay at points that imply they are willing to pay a positive amount of money to compete (on average €5.29). Conversely, 30% of participants switch at points that imply they are willing to pay money to avoid competing (on average €6.65). Given that average expected earnings are around €15, preferences for competition are clearly a non-negligible component of individuals' well-being in this type of context.

Our findings also reveal two other intriguing patterns. First, individuals become more competition loving when they compete in groups of six compared to groups of three. Second, we do not find that men are more competition loving than women. This suggests that, while preferences for competition do exist, the commonly reported gender difference in competition entry (Dariel et al., 2017) might be the result of gender differences in risk preferences and beliefs.

2 Literature review

This paper contributes to the literature on measuring preferences for competition. Starting with the seminal paper of Niederle and Vesterlund (2007), there have been many papers studying preferences for competition, especially in the context of gender differences (Niederle and Vesterlund, 2011; Niederle, 2017). Dariel et al. (2017) reviews the papers based on slight variations of the Niederle and Vesterlund (2007) experimental design. In Table A.1 in the Appendix, we list these papers and whether they differ from the original design. We also include a few more recent papers that share design choices with our experiment. We concentrate on three aspects of the experimental design: the way participants choose to compete, the method used to elicit beliefs, and the way risk preferences are elicited.

Most papers use one binary choice to measure preferences for competition. However, like us, some papers use an MPL. Petrie and Segal (2017) use an MPL to elicit the prices at which one obtains a gender balance in competition entry. In their experiment, participants choose seven times between individual and competitive pay. Individual pay is always \$0.50 per correct sum, while competitive pay varies from \$0.75 to \$2.25 per correct sum (for the group's winner). Ifcher and Zarghamee (2016) use a similar approach, but they keep competitive pay constant at \$2.00 per correct sum and vary individual pay from \$0.00 to \$2.00 per correct sum. Jung and Vranceanu (2019) also uses an MPL, but instead of varying prices per correct sum, they elicit the lump-sum payment that makes participants indifferent between individual and competitive pay. Saccardo et al. (2018) develop a continuous of preferences for competition. In their design, participants choose the percentage of their compensation derived from individual pay and the percentage derived from competitive pay. All these papers find that the choice to compete is sensitive to changes in incentives. In addition, they report considerable heterogeneity at the point at which individuals switch from individual to competitive pay. In terms of gender differences, these papers find men are more willing to compete than women, but there is substantial overlap. Namely, there is a considerable fraction of competition-loving women, and a noticeable fraction of competition-averse men. Compared to our paper, these papers use only one MPL, and their individual pay is not a lottery.[1]

There is also some variation in methods for belief elicitation in the literature on preferences for competition. As seen in Table A.1, most papers elicit beliefs by asking participants to guess their rank within their group and reward them with an additional payment if they guess correctly. The drawback of this method is that ranks do not map to a unique probability of winning the competition, which is necessary to calculate the participants' expected earnings from competing.[2] For this reason, we opted for directly eliciting the participants' expected probability of winning. A few other papers do so as well. Most of them also use a binarized scoring rule to incentivize participants to provide accurate responses (Berlin and Dargnies, 2016; Petrie and Segal, 2017; Reuben et al., 2017; Fallucchi et al., 2020; van Veldhuizen, 2022), while a couple chose not to incentivize at all (Buser et al., 2017b; Saccardo et al., 2018).[3] Although these papers can calculate the expected earnings of winning the competition, the fact that they use a binary decision to compete means that, unlike us, they cannot estimate the strength of the participants' preferences for competition. The exception is Saccardo et al. (2018), who use a continuous measure of competition entry and a (non-incentivized) measure of the probability of winning. We build on their work and use these design features to estimate the monetary equivalent of preferences for competition. In addition, since we have more than one competition-entry decision, we can study the consistency of these preferences.

To identify preferences for competition, one must also account for the effect of risk preferences. Most papers in this literature do so with an independent risk-preference elicitation task

[1] Another related paper is Dohmen and Falk (2011). In their paper, participants choose between a fixed payment (i.e., independent of performance) and a variable payment, which could be a piece rate, a tournament rate, or revenue sharing. In addition to their choice, participants use a hypothetical MPL to indicate their willingness to choose the variable payment.

[2] Other approaches include eliciting the participants' expected number of correct sums for themselves and/or others (e.g. Dargnies, 2012; Wozniak et al., 2014; Brandts et al., 2015), their self-reported assessment of their relative performance (e.g. Bönte et al., 2017; Buser et al., 2020), and their ranking within the session (e.g. Cárdenas et al., 2012). These approaches also cannot be easily mapped to a probability of winning the tournament.

[3] There is an ongoing discussion on the best way to describe the binarized scoring rule to participants. Danz et al. (2022) propose that simpler descriptions outperform more complex ones. We simplify the binarized scoring rule by giving participants an interactive graphical interface to calculate incentives and compute how a percentile ranking translates into the probability of winning the competition (see Section 3 for details).

such as the MPL of Holt and Laury (2002), the lottery choice of Eckel and Grossman (2002), the Bomb Risk Elicitation Task of Crosetto and Filippin (2013), or the self-reported question of Dohmen and Falk (2011) (see Table A.1). Another approach was introduced by Niederle and Vesterlund (2007). In this approach, participants are given an additional opportunity to be paid again for their past performance and can decide whether they want to be paid according to individual or competitive pay. Since Niederle and Vesterlund (2007) define preferences for competition as a preference to seek or avoid performing in competitive environments, they argue that this additional choice captures the riskiness of the competitive pay but is unaffected by preferences for competition. Differently from these papers, instead of accounting for risk preferences with a different task, we change the reward structure of individual pay to ensure that risk preferences do not play a role in the decision to compete. To our knowledge, Geraldes (2020) is the only other paper that uses a lottery as individual pay. However, our experimental design differs in multiple ways. For instance, Geraldes (2020) uses a single binary decision to compete and does not elicit beliefs with a proper scoring rule.

Lastly, two important papers question the existence of a gender gap in preferences for competition. Gillen et al. (2019) point out that identifying gender differences in preferences for competition by regressing the choice to compete on a gender dummy plus measures of risk preferences, beliefs, and performance can result in the overestimation of gender differences in preferences for competition due to measurement error in the control variables. They show that accounting for the noise in the measurement of the control variables reduces the magnitude and significance of the coefficient of the gender dummy in the Niederle and Vesterlund (2007) design. van Veldhuizen (2022) introduces new treatments that remove the role of competition and overconfidence from the decision to compete. He compares gender gaps in these treatments to that in the Niederle and Vesterlund (2007) design to identify under what conditions the gender gap in the decision to compete disappears. As Gillen et al. (2019), van Veldhuizen (2022) conclude that the gender gap in competition is mainly captured by gender differences in risk preferences and beliefs. Conceptually, our work differs from these papers in that we do not focus on identifying the sources of the gender difference in decisions to compete. Instead, we focus on measuring individuals' preferences for competition directly.

3 Experimental design

Our experiment is based on the experimental design developed by Niederle and Vesterlund (2007) to measure preferences for competition. As in their design, participants are randomly assigned to groups and perform an adding task.[4] The adding task consists in performing sums

[4]Unlike Niederle and Vesterlund (2007), in our experiment, participants cannot physically see others in their group. They simply know they are matched with other participants in the session.

of four two-digit numbers for four minutes. The integers are randomly drawn from a uniform distribution with support from 10 to 99. Participants are not allowed to use a calculator but are provided with scratch paper. The participant who correctly solves the highest number of sums in their group is the group's winner (ties are broken randomly). Our elicitation of preferences for competition is based on the following two tasks.

3.1 Belief elicitation task

In this task, participants report their belief of being their group's winner. We incentivize the belief elicitation using a robust scoring rule (Karni, 2009). Specifically, participants take part in a lottery for a prize of €20. The probability of getting the prize depends on their stated belief and whether they turn out to be their group's winner. Specifically, for a stated belief of being the winner b_i, participant i has a probability $1-(1-b_i)^2$ of getting the prize if i is the winner, and a probability $1-b_i^2$ if i is one of the losers. This belief elicitation method is easy to implement, incentive compatible for a wide range of risk preferences, and has been shown to outperform other elicitation methods (Gächter and Renner, 2010; Wang, 2011; Hossain and Okui, 2013; Harrison and Phillips, 2014; Trautmann and van de Kuilen, 2015). To facilitate understanding of the elicitation method, participants submit their beliefs using an interactive graphical interface that automatically calculates the probabilities of winning the prize and the associated expected earnings for any selected belief. In addition, we give participants easy-to-follow examples that illustrate why it is optimal to report truthfully. The instructions for this task are available in Appendix A.6 and include a screenshot of the graphical interface.

Another feature of our belief elicitation task is that participants can answer the belief elicitation question by indicating their expected percentile ranking in the performance distribution. Upon selecting a percentile, participants are shown the probability of being a winner in a randomly formed group. The advantage of this feature is that participants who struggle to calculate compound probabilities can answer in terms of an easy-to-understand ranking. We also provide participants with a table displaying the probability of being their group's winner for every percentile in the performance distribution (see the instructions in Appendix A.6).[5]

3.2 Payment-scheme choice and adding task

Before performing the adding task, participants choose how they want to be paid per correct sum. Specifically, they choose between *competitive pay* and *individual pay* in five independent decision sets. Each decision set is an MPL that contains ten rows, and each row is a choice

[5]The probabilities of being a group's winner are calculated assuming that participants in a session are randomly drawn from a performance distribution. We do not find that performance in the first or the second addition task varies by session (Kruskal-Wallis tests, $p > 0.118$ for groups of three and $p > 0.137$ for groups of six).

Table 1. Example of a decision set

Note: Example of a decision set with a high amount $\pi^H = 4$, a low amount $\pi^L = 1$, and a range of probabilities for individual pay between 0.17 to o.44.

	Competitive pay		**Individual pay**			
Row	**Win (€)**	**Lose (€)**	**Win (€)**	**P(Win)**	**Lose (€)**	**P(Lose)**
1	4	1	4	0.17	1	0.83
2	4	1	4	0.20	1	0.80
3	4	1	4	0.23	1	0.77
4	4	1	4	0.26	1	0.74
5	4	1	4	0.29	1	0.71
6	4	1	4	0.32	1	0.68
7	4	1	4	0.35	1	0.65
8	4	1	4	0.38	1	0.62
9	4	1	4	0.41	1	0.59
10	4	1	4	0.44	1	0.56

between competitive pay (left) and individual pay (right). After making their choices, one row from one decision set is randomly selected and implemented. Subsequently, participants perform the adding task knowing the decision set and row that was randomly selected.

Under competitive pay, participants earn a high amount π^H per correct sum if they are their group's winner and a low amount π^L per correct sum otherwise. Under individual pay, participants earn π^H per correct sum with some probability p and π^L per correct sum with probability $1-p$. Within a decision set, the probability of earning π^H in individual pay increases as one goes from the first to the tenth row. The values of π^H and π^L are constant within a decision set but vary across decision sets. Table 1 displays an example of a decision set where $\pi^H = 4$, $\pi^L = 1$, and p ranged from 0.17 to o.44.

3.3 Treatment variations

We use a 2×2 treatment design. The first treatment variation consists of varying the timing of the belief elicitation task. In treatment *Belief-first*, participants first do the belief elicitation task, followed by the payment-scheme choice, and ending with the adding task. In treatment *Choice-first*, participants first make the payment-scheme choice, followed by the adding task, and ending with the belief elicitation task. This treatment variation serves as a robustness check to see whether our proposed method to elicit preferences for competition is sensitive to the sequence in which beliefs and choices are elicited. Most papers in the literature on preferences for competition elicit beliefs after the decision to compete (as in Niederle and Vesterlund, 2007). A few papers elicit beliefs before this decision (e.g., Mayr et al., 2012; Almås et al., 2016; Buser et al., 2020; van Veldhuizen, 2022) but to the best of our knowledge, this is the only paper where participants are randomly assigned to *Belief-first* and *Choice-first* treatments.[6] We implement this treatment variation between subjects.

Notably, the timing at which we elicit beliefs also affects how we construct the MPLs of the payment-scheme choice. There are two desirable conditions for us to measure preferences for competition with a reasonable degree of accuracy. First, the change in the probabilities from one row to the next in the MPLs is not too large. Second, the participants' belief of being their group's winner is contained within the range of probabilities in the MPLs. To help meet these conditions, the probabilities in the MPLs are based on previous stages. Specifically, in treatment *Belief-first*, the range of probabilities in the MPLs is centered around the participants' elicited belief of being their group's winner. In treatment *Choice-first*, we narrow down the range of probabilities by giving participants two additional decision sets in which they choose between competitive and individual pay. In the first additional decision set, the probabilities for individual pay range from 0.05 to 0.95 in steps of 0.10. Based on the number of times a participant chooses competitive pay in that first set, the probabilities for individual pay in the second additional set range from either 0.05 to 0.50, 0.30 to 0.70, or 0.50 to 0.95 in steps of 0.05. The five decision sets used to measure preferences for competition are centered around the probability at which participants switch from competitive pay to individual pay in this second additional decision set. Across decision sets, we randomize the position of the belief or switching probability from two rows above to two rows below the fifth row of the MPL. This way, participants face a different range of probabilities across decision sets.[7] Appendix A.2 contains a more detailed description of the procedure used to determine the probabilities in individual pay and the high and low amounts in each decision set.

The second treatment variation consists of varying the size of the group in which participants compete. We implemented groups of *three* and *six* participants. This treatment variation allows us to evaluate the role of the number of competitors in shaping individual preferences for competition. This treatment variation is implemented within subjects. In other words, all participants do the belief elicitation task, payment-scheme choice, and adding task twice, once for a group of three and once for a group of six. The order of the group size is counterbalanced across sessions. Moreover, note that participants do not receive feedback on their relative performance until the end of the experiment.

[6] Some papers measure beliefs both before and after the choice to compete, but they also give participants feedback on their relative performance (e.g., Berlin and Dargnies, 2016). In Appendix A.1 we provide a list of papers that follow the design of Niederle and Vesterlund (2007) and describe their preferences for competition, beliefs, and risk preferences elicitation methods.

[7] As with many elicitation methods (e.g., van de Kuilen and Wakker, 2011; Toubia et al., 2013; Chapman et al., 2019), participants are not explained how their previous choice affects future decision sets.

3.4 Experimental procedures

The experiment was conducted at the Behavioral and Experimental Economics Laboratory (BEElab) at Maastricht University. We ran in 11 sessions with a total of 224 participants (133 women and 91 men). We recruited participants with the online recruitment system ORSEE (Greiner, 2015) and the experiment was programmed and run with z-Tree (Fischbacher, 2007).

All participants signed an informed consent form before participating in the experiment. The experiment consisted of five parts: the two belief elicitation tasks, the two payment-schemes choices with their respective addition tasks, and a final risk-elicitation task. Instructions for each task were provided at the beginning of the respective task. At the end of the experiment, one part was randomly selected for payment. In addition, participants had an unincentivized practice round of three minutes to familiarize themselves with the adding task and completed a demographics questionnaire that included gender, age, and information about their siblings, nationality, and education. On average, participants received €25 (including a €10 show-up fee). The instructions for the experiment can be found in Appendix A.6.

4 Measuring preferences for competition

In this section, we describe the conceptual framework used to measure preferences for competition. We assume that participants' preferences can be represented by a utility function $U(\pi_i, C)$ that depends on the monetary payoffs π and whether a participant is performing under competitive ($C = 1$) or individual ($C = 0$) pay. More specifically, We assume the following utility function for participant i:

$$U(\pi_i, C) = u(\pi_i) + C\theta_i,$$

where π_i is the monetary value of performing the task (i.e., i's number of correct sums multiplied by either π^H or π^L) and θ_i is the parameter that captures i's non-pecuniary utility of performing under competition. As usual, we assume $u'(\pi_i) > 0$ and individual risk preferences are represented by the curvature of the utility function, $u''(\pi_i)$. Hence, we assume separability between preferences for competition and risk.

Under these assumptions, i is indifferent between competitive and individual pay if

$$\begin{aligned} b_i u\big(x_i \cdot \pi^H\big) + (1 - b_i) u\big(x_i \cdot \pi^L\big) + \theta_i &= p u\big(x_i \cdot \pi^H\big) + (1 - p) u\big(x_i \cdot \pi_i^L\big) \\ \theta_i &= (p - b_i)\big[u\big(x_i \cdot \pi^H\big) - u\big(x_i \cdot \pi^L\big)\big], \end{aligned}$$

where b_i is i's belief of being the winner of their group in the competitive pay, p is the probability of obtaining π^H in individual pay, and x_i is i's expected number of correct sums in the addition task. Note that using the same π^H and π^L for both payment schemes ensures that we can solve for θ_i irrespective of i's risk preferences. This feature of our design addresses some of the concerns raised by Gillen et al. (2019) and van Veldhuizen (2022) as our setting does not rely on assuming that risk and competitive preferences are orthogonal.

We measure preferences for competition by comparing the probability at which i is indifferent between competitive and individual pay, p_i, with i's belief of being the group's winner, b_i. Intuitively, if $p_i > b_i$, then i is giving up a higher chance of winning a large amount under individual pay for a lower chance of winning the same amount under competitive pay, implying that i must 'like' competing. Conversely, if $p_i < b_i$, then i is giving up a higher chance of winning under competitive pay for a lower chance of winning under individual pay, implying that i must 'dislike' competing. More precisely, for a participant i in decision set t, we calculate:

$$\omega_{it} = (p_{it} - b_i)\big(\pi^H - \pi^L\big)\hat{x}_i,$$

where ω_{it} as i's willingness to pay to perform under competitive pay, p_{it} is the midpoint between the probability of the row at which i switched from competitive pay to individual pay and the probability of the preceding row, b_i is i's reported belief of being their group's winner, and $\hat{x}_i$ is i's number of correct sums in the adding task.[8] An $\omega_{it} > 0$ implies i is competition loving whereas $\omega_{it} < 0$ implies i is competition averse.

5 Results

Descriptive statistics of the participants' performance in the adding task, their beliefs of being their group's winner, and their degree of overconfidence are presented in Table A3 in the Appendix. On average, participants correctly answer 11.4 sums and believe they have a 44.9% chance of winning, which means they are overconfident as they overestimate their chances of winning by 19.9%.[9] If we look at treatment differences, we find that beliefs of being the group's winner systematically change between group sizes in the expected direction: higher beliefs of winning in groups of three than in groups of six (on average, 53.8% vs. 36.0%). Group size does not affect performance in the adding task (11.4 vs. 11.3 sums) or the participants' overconfidence (20.4% vs. 19.4%).[10] Unlike group size, the moment at which beliefs are elicited does not have a noticeable effect. On average, participants in the *Belief-first* and *Choice-first*

[8] By using the realized number of correct sums, we measure the monetary amount participants end up paying to seek or avoid competition. To measure the monetary amount participants expect to pay, one must also elicit their expected number of correct sums. We did not elicit these beliefs as the experiment is already overly complex. We discuss this further in Section 6.

[9] To measure overconfidence, we simulate each participant's probability of winning by rematching participants 100,000 times into groups of three or six to observe how often each participant wins, given their observed performance in a particular group size. Overconfidence is calculated as the participants' belief of being their group's winner minus their estimated probability of winning.

[10] Participants' beliefs of being their group's winner are significantly higher in groups of three than in groups of six in both the *Belief-first* and *Choice-first* treatments (Wilcoxon signed-rank tests, $p < 0.001$ in both cases). By

Table 2. Consistency of switching behavior within decision sets

Note: Fraction of decision sets with inconsistent behavior: with either *multiple switches* or a single *non-monotonic switch* from individual to competitive pay. Fraction of decision sets with consistent behavior with either a *single switch* from competitive to individual pay or *no switch*. For each group size, there are 224 participants and a total number of decision sets of 1120.

	Group Size	
	Three	Six
Inconsistent behavior		
Multiple switches	3.1%	3.9%
Non-monotonic switch	1.0%	0.7%
Consistent behavior		
Single switch	77.0%	76.0%
No switch	18.9%	19.4%

treatments exhibit similar beliefs of being their group's winner (42.6% vs. 47.0%), performance in the adding task (10.9 vs. 11.7 sums), and overconfidence (19.7% vs. 20.1%).[11] Due to these findings, we analyze the participants' preferences for competition separately for groups of three and six, but we pool the data for the *Belief-first* and *Choice-first* treatments. In Appendix A.5, we present the results separately for these treatments as one of the robustness checks. The results are not quantitatively different with the ungrouped data.[12]

5.1 Switching behavior

Since we did not impose a single-switch restriction in the decision sets, we can test whether behavior within sets is consistent with utility maximization in the absence of errors by looking at the number of times and the direction in which participants switch within a decision set. Specifically, we categorize behavior within decision sets as *inconsistent* if there are multiple switches or a unique non-monotonic switch, meaning a switch from the payment scheme with the higher expected value (individual pay) to the one with the lower expected value (competitive pay). Similarly, we categorize behavior within decision sets as *consistent* if there is one switch from competitive to individual pay (single switch) or if all choices correspond to either competitive or individual pay (no switch).

Table 2 displays the fraction of consistent and inconsistent decision sets for the two group

contrast, there are no statistically significant differences in the number of correct sums (Wilcoxon signed-rank tests, $p > 0.928$) or overconfidence (Wilcoxon signed-rank tests, $p > 0.610$).

[11] In both group sizes, there are no statistically significant differences between *Belief-first* and *Choice-first* in the number of correct sums (Mann-Whitney U tests, $p > 0.396$), the belief of being the group's winner (Mann-Whitney U tests, $p > 0.144$), and the degree of overconfidence (Mann-Whitney U tests, $p > 0.657$).

[12] The order in which participants face the two group sizes is counterbalanced. Hence, we pool together both orders for the main analysis. However, for robustness, we show in Appendix A.5 that the paper's main results are unaffected by considering each order separately.

Table 3. Consistency of switching behavior across decision sets

Note: Fraction of participants with inconsistent switching behavior in at least one decision set. For participants with consistent behavior in all five decision sets, the table also displays the fraction of participants with a single consistent switch in a majority of decision sets (three or more) and the fraction who switch consistently in all five decision sets. For each group size, the total number of participants is 240.

	Group Size	
	Three	Six
Inconsistent behavior		
At least one set with inconsistent switching behavior	8.9%	11.6%
Consistent behavior		
All sets with consistent switching behavior	91.1%	88.4%
All sets with consistent switching behavior and a single switch in a majority of sets	75.9%	75.0%
All sets with consistent switching behavior and a single switch in all five sets	54.5%	45.5%

sizes. When participants compete in groups of three, we observe around 96% of the decision sets display consistent switching behavior, with 77% of sets having a single switch and 19% having no switch. An almost identical pattern is present in groups of six. Namely, 95% of decision sets exhibit consistent behavior, with 76% having a single switch and 19% having no switch.[13]

Next, we look at participants' switching behavior across the five decision sets. The top section of Table 3 shows the percentage of participants with at least one inconsistent decision set. We can see that this is a small minority of 9% when competing in groups of three and 12% when competing in groups of six. In other words, the vast majority of participants display consistent switching behavior in all five sets (91% in groups of three and 88% in groups of six).

We continue by looking at consistent switching behavior, distinguishing between sets with a single switch and no switch. The reason is that to measure a precise value for participants' willingness to pay to compete, we need to observe a switch from competitive to individual pay. The bottom section of Table 3 shows the percentage of participants who have a consistent single switch in a majority of sets (three or more) as well as the percentage who switch consistently in all five sets. In both group sizes, around three-quarters of participants switch once from competitive to individual pay in a majority of sets, and around half do so in all five sets.[14]

To sum up, participants' choices to compete are highly consistent with utility maximization. In almost all decision sets, they either switch once from competitive to individual pay or do not switch at all. Remarkably, around 90% of the participants display this type of consistent behavior in all five decision sets.

[13] The number of inconsistent sets per participant is not significantly different across group sizes (Wilcoxon signed-rank test, $p = 0.255$).

[14] The fraction of participants with at least one inconsistent decision set does not vary significantly across group sizes (McNemar's χ^2 test, $p = 0.327$). The same is true for the fraction of participants who switch consistently in a majority of sets (McNemar's χ^2 test, $p = 0.894$). The fraction of participants who switch consistently in all sets is significantly higher in groups of three (McNemar's χ^2 test, $p = 0.033$).

5.2 Willingness to pay to compete

In this subsection, we look at the participants' willingness to pay to compete by analyzing the location of their switching points. To ensure that we obtain an accurate measure of willingness to pay to compete, we concentrate solely on participants who had no inconsistent behavior in any decision set and switched consistently in the majority of sets. Namely, 76% of participants in groups of three (170 out 224) and 75% of participants in groups of six (168 out 224). In Appendix A.5, we test the sensitivity of our results to this restriction. Tables A6 and A7 present the main results when we include participants who switched consistently in less than three sets and when we add participants with inconsistent behavior in some decision sets.

We summarize a participant's willingness to pay to perform under competitive pay by calculating the median value of the five ω_{it}s, which we denote as $\bar{\omega}_i$ (see section 4).[15] If participants derive non-pecuniary utility from performing under competitive pay, we should observe values of $\bar{\omega}_i$ that are noticeably different from zero.

Figure 1 displays the distribution of $\bar{\omega}_i$ for the two different group sizes. The figure shows that most participants have a nonzero $\bar{\omega}_i$. For example, 63% of participants in groups of three and 82% in groups of six have a value of $\bar{\omega}_i$ that is greater than €1.00 in absolute terms. In other words, a majority of participants are willing to give up money to either compete or avoid competing. For groups of three, the mean value of $\bar{\omega}_i$ is −€0.65 (s.d. €5.46) and for groups of six it is €1.22 (s.d. €8.66).

Figure 1 shows that increasing the number of competitors makes participants more competitive. A Wilcoxon signed-rank test shows that the distribution of $\bar{\omega}_i$ varies significantly between groups of three and groups of six ($p < 0.001$). Moreover, the figure also shows that when participants compete in groups of six, the variance of the distribution of $\bar{\omega}_i$ is larger (Levene's equality of variances test, $p < 0.001$) and there are fewer participants with a value of $\bar{\omega}_i$ that is close to zero (McNemar's χ^2 test, $p < 0.001$). These findings suggest that when participants are in a more competitive setting, they are more likely to display a stronger preference for either liking or disliking competition.

5.3 Additional analyses

Next, we run a series of additional analyses to investigate whether our measure of the participants' preferences for competition truly reflects their preferences or whether it is confounded by decision error. As before, we conduct the analyses using the participants who had no inconsistent behavior in any decision set and switched consistently in the majority of sets.

[15] Similar results are obtained if we use the mean value of the ω_{it}s (see Appendix A.4). However, since we restrict our sample to participants who switched consistently in the majority of sets, using the median guarantees that a participant's $\bar{\omega}_i$ is based on a decision set that contains a switch from competitive to individual pay.

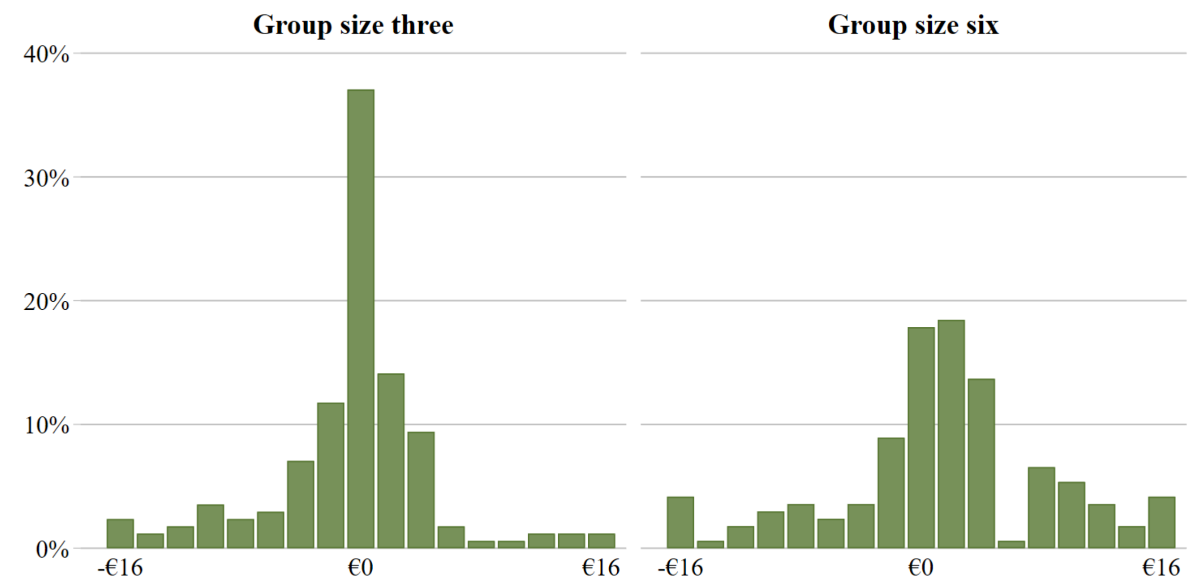


Figure 1. Distribution of participants' willingness to pay to compete ($\bar{\omega}_i$) by group size

Note: For visual ease, Figure 1 censors the values of $\bar{\omega}_i$ at -16 and 16. The percentage of participants that fall outside this range is 2% in groups of three (3 out of 170 participants) and 7% for groups of six (11 out of 168 participants).

Variation between vs. within participants

As a first step, we look at the extent to which variation in our measure of preferences for competition is explained by variation within participants versus variation between participants. The intuition is that if participants' choices are driven mostly by (uncorrelated) decision errors instead of differences in an underlying preference, then we should find relatively high variation in choices within participants compared to variation between participants. Conversely, if the impact of decision errors is minimal, then we should find that choices vary little within participants relative to the variation between participants. Since we have five sets per participant and group size, we can do a total variance decomposition analysis using the values of ω_{it}. We find that the within-participant variation is smaller than the between-participants variation. Specifically, 74% of the total variation in the values of ω_{it} is due to between-participant variation in groups of three and 79% in groups of six.[16]

Persistence of competition-loving and competition-averse behavior

As a next step, we analyze the persistence of competition-loving or competition-averse behavior across the five decision sets.

As seen in Table 2, participants make very few mistakes in terms of switching behavior within decision sets. However, another way of thinking of mistakes is to consider the possibility

[16]The fraction of the total variance accounted for by variance between participants corresponds to the R^2 of an OLS regression of ω_{it} on the set of individual dummies.

that a participant has a consistent switch within a set, but it occurs in the wrong row in the MPL. For example, suppose that participants do not have preferences for competition. In this case, they should switch to individual pay at row r^*_{it}, defined as the highest row where a participant's belief of being the group's winner exceeds the probability of getting the high amount in individual pay in set t. However, they could still show high positive or negative values of $\omega_{i,t}$ in a decision set if they mistakenly switch at rows below or above r^*_{it}. If we further assume that a switching mistake is equally likely at rows above or below r^*_{it}, then we should not observe a high fraction of participants switching persistently in the same direction. Next, we classify participants as persistently competition loving if they switch at rows above r^*_{it} in at least 4 out of 5 sets. Analogously, we classify participants as persistently competition averse if they switch at rows below r^*_{it} in at least 4 out of 5 sets. The remaining participants are classified as 'not defined.'

Table 4 displays the percentage of participants who are persistently competition loving, persistently competition averse, and 'not defined.' Overall, a considerable majority of participants are either persistently competition loving or persistently competition averse. Specifically, 71% when competing in groups of three and 74% when competing in groups of six. As a benchmark, consider the extreme scenario where participants do not have preferences for competition, but they always make a mistake and switch at a row above or below r^*_{it}, each with 50% probability, in all decision sets. In this hypothetical scenario, one would observe around 19% of participants classified as persistently competition loving, another 19% classified as persistently competition averse, and 62% as classified as not defined.[17] In other words, we observe much more persistent behavior than that predicted by mistakes alone (the observed and hypothetical distributions are significantly different; Pearson's χ^2 tests, $p < 0.001$).

Table 4 also reveals that, while the fraction of participants classified as not defined is similar across group sizes, participants are more persistently competition loving in groups of six compared to groups of three (Wilcoxon signed-rank test, $p = 0.013$).

Noise in belief elicitation

Our measure of preferences for competition relies on an accurate measurement of the participants' belief of being their group's winner. Hence, one might worry that the variation in $\omega_{i,t}$ is capturing variation due to noise in the measurement of beliefs instead of differences in preferences for competition. We conduct two analyses to evaluate whether noise in belief measurement is driving our results.

[17] More generally, suppose that the probability that participant i switches at a wrong row is $q_i \in [0,1]$ and that conditional on making a mistake switching above or below r^*_{it} is equally likely. In this case, the probability that i switches at a row above r^*_{it} in x sets out of five is given by $\sum_{y=1}^{5} f(x, y, 0.5) \times f(y, 5, q_i)$, where $f(.)$ is the probability mass function of the Binomial distribution.

Table 4. Persistently competition-loving or competition-averse participants

Note: Percentage of participants who are persistently competition loving, defined as switching at rows above r^*_{it} in at least 4 out of 5 sets, or competition averse, switching at rows below r^*_{it} in at least 4 out of 5 sets, where r^*_{it} is the highest row where a participant's belief of being the group's winner exceeds the probability of getting the high amount in individual pay. The remaining participants are classified as 'not defined.' 170 participants for groups of three and 168 for groups of six.

	Group size	
	Three	Six
Persistently competition loving	36.5%	51.2%
Persistently competition averse	34.7%	23.2%
Persistently competition loving or competition averse	71.2%	74.4%
Not defined	28.8%	25.6%

First, we check whether variance in beliefs correlates with variance in preferences for competition. For this analysis, we utilize the fact that we have two measures of beliefs per participant (one for each group size) and that we elicited beliefs both as the probability of being the group's winner and the expected percentile ranking in the performance distribution. Although the probability of being the group's winner mechanically decreases as one goes from groups of three to groups of six, the associated percentile ranking does not. Hence, an interpretation of observing a difference in a participant's expected percentile ranking is that there is measurement error in beliefs. Using this interpretation, we classify participants as having noisy beliefs if the absolute difference between the two expected percentile rankings is larger than the median. If the variation in $\omega_{i,t}$ is mostly due to noise in belief measurement, we should observe higher variation in $\omega_{i,t}$ for participants with noisy beliefs compared to the rest.

Interestingly, we do not observe significantly more variation in $\omega_{i,t}$ for participants with noisy beliefs. In groups of three, the standard deviation of $\omega_{i,t}$ for participants with noisy beliefs equals €5.25 while that for participants without noisy beliefs is €5.58 (Levene's equality of variances test, $p = 0.206$). In groups of six, the corresponding standard deviations are €8.50 and €8.84 (Levene's equality of variances test, $p = 0.680$). Hence, we do not find evidence that variation in our measure of preferences for competition is driven by variation in beliefs.

Our second analysis is based on the insights of Danz et al. (2022), who show that incentivized belief elicitation using the binarized scoring rule in some instances leads to a systematic center-bias in belief measurement. In our experiment, their findings imply that participants whose 'true' belief of being their group's winner is above 50% will tend to report a belief b'_i that is too low, $0.50 \leq b'_i \leq b_i$. Conversely, participants whose 'true' belief is below 50% will tend to report a belief that is too high, $b_i \leq b'_i \leq 0.50$. While it is not possible to test directly whether subjective beliefs are biased, a systematic center bias does have testable implications. Specifically, we would be overestimating ω_{it} for participants with beliefs above 50%, making them look more competition loving. Conversely, we would be underestimating ω_{it} for participants with beliefs below 50%, making them look more competition averse. We check for evidence of this effect by testing whether participants with beliefs above 50% have higher values of ω_{it} than participants with beliefs below 50%. We observe the opposite pattern. In both group sizes, participants with beliefs of being their group's winner above 50% have lower values of ω_{it} than those with beliefs below 50% (Mann-Whitney U tests, $p < 0.001$).[18] Hence, we do not find evidence that our measure of preferences for competition is actually capturing belief distortions due to incentivization Danz et al. (2022).

Overall, the results from this section suggest that the participants' willingness to pay to compete, ω_{it}, is describing their preferences for competition and not decision error.

5.4 Gender differences

While the main focus of this paper is on the measurement of preferences for competition, one of the reasons there has been considerable interest in this literature is the commonly-observed gender difference in competition entry (e.g., see Niederle, 2017; Dariel et al., 2017). Hence, we report below whether there are gender differences in the variables analyzed above. Before comparing the willingness to pay to compete between men and women, we first test whether there are gender differences in the consistency of switching behavior within and across decision sets.

We do not find significant gender differences in the fraction of decision sets displaying consistent switching behavior. Around 97% of the decision sets of men are consistent (75% have a single switch and 22% have no switch), while for women it is 95% (78% have a single switch and 17% have no switch; see Table A4; Mann-Whitney U tests, $p > 0.331$). Similarly, we do not find gender differences in consistency across sets. Around 75% of men and 76% of women have a consistent single switch in a majority of sets (see Table A5; Pearson's χ^2 tests, $p > 0.512$).

Next, we turn to gender differences in preferences for competition. As before, this analysis is based on participants with a consistent single switch in a majority of sets. Figure 2 displays the distribution of $\bar{\omega}_i$ by gender. The distributions are very similar. For groups of three, the mean value of $\bar{\omega}_i$ is −€1.54 (s.d. €5.25) for men and −€0.07 (s.d. €5.55) for women. For groups of six, the corresponding means are €1.17 (s.d. €9.10) for men and €1.25 (s.d. €8.38) for women.

We do not find statistically significant gender differences in the distributions of $\bar{\omega}_i$ for either group size (Mann-Whitney U tests, $p > 0.115$). Moreover, we do not find that gender matters for the effect of group size on preferences for competition, or in the various additional analyses

[18] We exclude from this analysis participants with beliefs equal to 50% (15 participants in groups of three and 6 participants in groups of six). We obtain the same result if we regress ω_{it} on a dummy variable indicating whether a participant's belief is above 50% and controls for the number of correct sums and distance between the participant's belief and 50%.

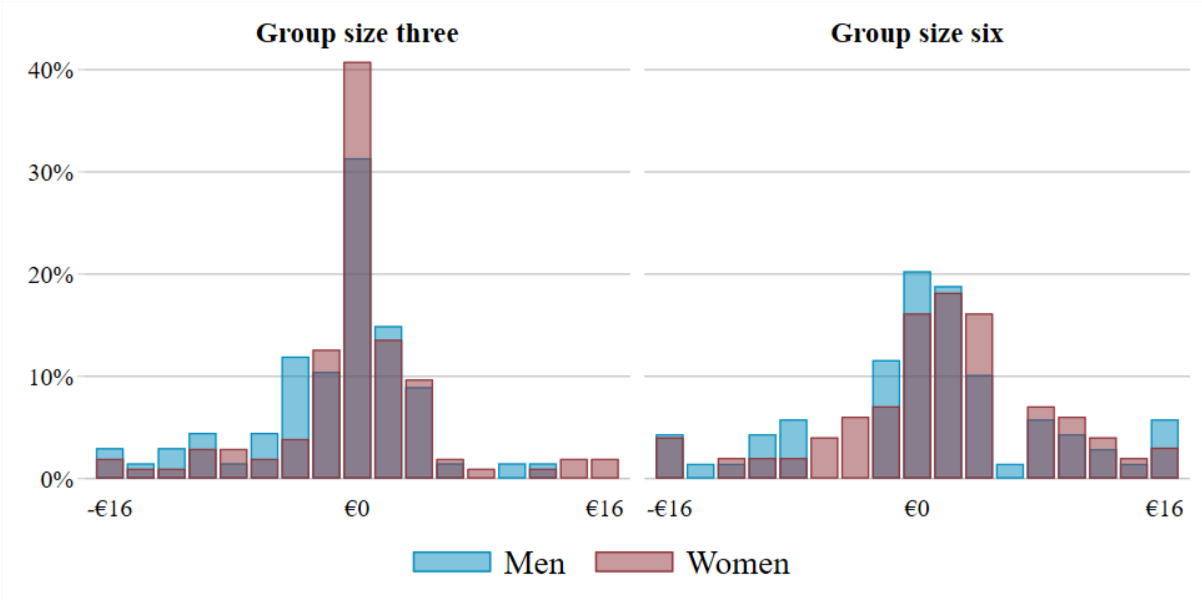


Figure 2. Distribution of participants' willingness to pay to compete ($\bar{\omega}_i$) by gender

Note: For visual ease, Figure 2 censors the values of $\bar{\omega}_i$ at -16 and 16. The percentage of participants that fall outside this range is 2% in groups of three (3 out of 170 participants) and 7% for groups of six (11 out of 168 participants).

reported above.[19] In short, we do not find evidence of gender differences in preferences for competition in our setting.

Could the lack of a gender difference be due to our subject pool? While gender differences in competition entry are often found with subject pools like ours, composed of university students, there are exceptions (e.g., see Dariel et al., 2017). As described in section 3, to obtain accurate individual measures of preferences for competition, our participants face choices between individual and competitive pay that depend on their decisions in previous stages. Hence, since participants encounter different decision sets, we cannot look at gender differences in competition entry in the five decision sets used to measure preferences for competition. However, in the *Choice-first* treatment, participants complete two additional decision sets where everyone faces the same ten choices between individual and competitive pay (choices in these decision sets varied the probability of winning in individual pay from 0.05 to 0.95). These decision sets are used to narrow down the range of probabilities in subsequent sets, but we can also use them

[19] Both men and women show significantly higher values of $\bar{\omega}_i$ in groups of six (Wilcoxon signed ranked tests, $p < 0.011$), but the difference does not vary significantly by gender (Mann-Whitney U test, $p = 0.932$). The percentage of total variation in ω_{it} due to between-participant variation equals 72% for men and 75% for women in groups of three and 80% for men and 77% for women in groups of six. Men and women are similarly likely to be persistently competition loving or persistently competition averse (see Table A7; Pearson's χ^2 tests, $p > 0.230$). Finally, men and women with noisy beliefs do not show more variation in $\omega_{i,t}$ than their less-noisy counterparts (Levene's equality of variances tests, $p > 0.761$), and men and women whose beliefs of winning are above 50% have lower values of ω_{it} than men and women with beliefs below 50% (Mann-Whitney U tests, $p < 0.001$).

Table 5. Choice of competitive pay in additional decision sets of the *Choice-first* treatment

Note: Linear probability regressions of the competition entry choice in the additional decision sets of the *Choice-first* treatment. The dependent variable equals one if a participant chooses competitive pay and zero if they choose individual pay. Each decision set contains ten choices. Controls in columns IV to VI correspond to group size and order dummy variables. All regressions include participant random effects. Only data from sets in which participants made consistent switching decisions are included. Standard errors clustered on participants are shown in parentheses. ***, **, and * indicate statistical significance at 0.01, 0.05, and 0.10.

	I	II	III	IV	V	VI
Woman	−0.080***	−0.045	−0.019	−0.079***	−0.044	−0.018
	(0.031)	(0.029)	(0.019)	(0.031)	(0.029)	(0.019)
Belief of being their		0.086***	0.161***		0.084***	0.161***
group's winner		(0.023)	(0.019)		(0.023)	(0.019)
Number of correct		0.000	0.002		0.001	0.002
sums		(0.018)	(0.014)		(0.018)	(0.013)
Willingness to pay to			0.0135***			0.136***
compete ($\bar{\omega}_i$)			(0.023)			(0.023)
Probability of winning	−1.300***	−1.300***	−1.300***			
in individual pay	(0.024)	(0.024)	(0.024)			
Controls	No	No	No	Yes	Yes	Yes
Observations	2280	2280	2280	2280	2280	2280
Participants	117	117	117	117	117	117
R^2	0.564	0.583	0.623	0.597	0.616	0.656

to compare the competition entry decisions of men and women.

Across the ten choices in the additional decision sets, men choose competitive pay 54% of the time whereas women choose competitive pay 46% of the time. In Table 5, we test whether this gender difference in competition entry is statistically significant. Specifically, we run linear probability regressions with the participants' choice of competitive pay in each row of the additional decision sets as the dependent variable. In all regressions, we include participant random effects and use clustered standard errors. Continuous variables are standardized to have a mean of zero and a standard deviation of one. Lastly, we restrict the sample to decision sets in which participants' exhibited a consistent switching behavior.

In column I, as independent variables, we include a gender dummy variable and the rows' probability of winning in individual pay. We find that women are significantly less likely to choose competitive pay than men. As one would expect, we also find that higher probabilities of winning in individual pay have a strong negative effect on the likelihood of choosing competitive pay. In column II, we include as dependent variables the participants' belief of being their group's winner and their performance in the adding task. Beliefs of being their group's winner have a strong significantly positive effect on the likelihood of choosing competitive pay. Interestingly, once we control for the participants' beliefs, the coefficient of the gender dummy is smaller and no longer statistically significant.[20] In column III, we also include the participants'

[20]Other papers doing a similar analysis typically control for the participants' risk preferences since in the original

willingness to pay to compete. Reassuringly, the participants' value of $\bar{\omega}_i$ is a strong predictor of their choice to compete in the additional decision sets. Controlling for $\bar{\omega}_i$ further reduces the coefficient of the gender dummy. In columns IV, V, and VI, we rerun the same regressions, but we control for the rows' probability of winning in individual pay in a more flexible way by including row fixed effects. In these regressions, we also include controls for group size and the order of play. The results are unchanged.

In sum, in line with most of the literature on competition entry, we find that women choose to compete less frequently than men. However, consistent with Gillen et al. (2019) and van Veldhuizen (2022), we find that the gender difference in competition entry disappears once we control for risk preferences and beliefs.

6 Conclusions

In this study, we further our understanding of the factors that drive competition-entry decisions by measuring the degree to which individuals enjoy or dislike performing in competitive environments. In other words, we measure their preferences for competition. Our findings provide compelling evidence that most participants are prepared to relinquish a sizable fraction of their expected earnings to either partake in or abstain from competition. Additionally, our results demonstrate that decisions regarding competition entry are highly consistent with expected utility maximization, and most individuals are either persistently competition loving or persistently competition averse.

To measure preferences for competition, we adjust the experimental paradigm developed by Niederle and Vesterlund (2007) in three important ways. First, we introduce probabilistic incentives when participants do not compete so that their competition-entry choice is unaffected by their risk preferences. Second, we obtain an accurate measure of the participants' belief of winning the competition using an intuitive graphical interface and an incentive-compatible elicitation method. Third, we record competition-entry decisions of each participant multiple times, each time using a multiple price list, enabling us to evaluate the consistency of participants' choices and whether they exhibit a persistent inclination or disinclination to compete.

One of the intriguing findings of our study is that participants' preferences for competition vary with the intensity of competition, as determined by the number of competitors. On average, participants are more competition loving when competing in groups of six compared to groups of three. To our knowledge, there have been few attempts to test the role of group size on competition-entry decisions. In the literature on contests, a small number of papers have looked

design of Niederle and Vesterlund (2007) competitive pay implies more risk than individual pay (for a discussion, see Lozano et al., 2023). In our design, competitive and individual pay both imply a risky choice with identical outcomes. Hence, risk preferences do not play a role (see section 3).

at the impact of group size (Dechenaux et al., 2015).[21] While larger group sizes don't necessarily lead to higher effort levels, it is telling that the gap between observed and predicted effort grows with the number of competitors (e.g., see Sheremeta, 2011; Lim et al., 2014). Accounting for preferences for competition may explain this finding. We also find that the more competitive setting induces higher variance in preferences across individuals, which suggests that the non-pecuniary utility from competition becomes more salient in more competitive environments.

An important confound when measuring preferences is the bias introduced by decision and measurement errors. While no experimental design can fully rule these biases, our robustness checks suggest that our findings are not the result of mistakes or noisy measurements (Gillen et al., 2019). First, we find a negligible fraction of violations of expected utility maximization in participants' switching behavior. Second, we observe that the within-participant variation in the willingness to pay to compete is much smaller than the between-participant variation, suggesting low levels of decision error compared to differences in preferences. Third, we find that most participants display behavior that is either persistently competition loving or persistently competition averse, which is highly unlikely if participants commonly make mistakes at the switching point between competitive and individual pay. Fourth, we show that our results are inconsistent with the patterns one should expect if there are substantial errors in the measurement of beliefs. Namely, we show that variation in beliefs within participants does not explain variation in the willingness to pay to compete between participants and that willingness to pay to compete is not positively correlated with beliefs, which would be the case if the elicited beliefs are systematically centered biased (Danz et al., 2022).

Although our experimental design has numerous advantages, it does have some drawbacks. An obvious limitation is that we ask participants to make a substantial number of choices based on relatively lengthy and detailed instructions. This means that our design is well-suited to measure preferences for competition in the lab but might not be ideal for samples that are less attentive or have time constraints, such as many online samples or large surveys (for these samples see, Buser et al., 2020; Fallucchi et al., 2020) Another limitation is that we estimate the participants' willingness to pay to compete using their actual performance in the adding task. We did this to avoid asking participants for one additional belief. It is unclear whether participants systematically overestimate or underestimate their absolute performance. The literature on preferences for competition has mostly focused on beliefs about relative performance (see Table A.1). However, when reported, it appears that participants tend to slightly overestimate the number of sums they will answer (Kamas and Preston, 2012; Wozniak et al., 2014; Banerjee et al., 2018; Saccardo et al., 2018). If this is the case with our

[21] There are also studies studying competition entry decisions where the number of competitors is unknown at the time the entry decision is made (e.g., Morgan et al., 2012). It is unclear how our finding translates to settings where the number of competitors is endogenous.

participants, we would be slightly underestimating the absolute value of their willingness to pay to compete.

In the last part of our analysis, we look at gender differences. We find that men and women are equally consistent in their switching behavior, are similarly likely to be persistently competition loving or competition averse, and are willing to pay comparable amounts to either take part or avoid competing. The latter finding is in line with Gillen et al. (2019) and van Veldhuizen (2022) who report that gender differences in competition entry vanish after accounting for risk preferences and beliefs. Importantly, unlike these papers, we show that the lack of gender difference is not due to nonexistent preferences for competition. In fact, our findings suggest that preferences for competition are widespread and distinct from risk preferences, as suggested by empirical work showing that competition and risk-taking behavior in the lab predicts different behaviors in the field (e.g., Buser et al., 2014; Reuben et al., 2017, 2019; Buser et al., 2020).

In sum, we find that preferences for competition are prevalent among our participants and an important determinant of their competitive behavior. Given the ubiquity of competition in our lives, comprehending individuals' motivations to compete is crucial. For example, the notion that non-pecuniary factors unrelated to performance can drive decisions to compete may impact the predicted efficacy of competitions in recognizing top performers or affect the welfare implications of tournaments.

References

Almås, I., Cappelen, A. W., Salvanes, K. G., Sørensen, E. Ø., and Tungodden, B. (2016). Willingness to Compete: Family Matters. *Management Science*, 62(8):2149–2162.

Andersen, S., Ertac, S., Gneezy, U., List, J. A., and Maximiano, S. (2013). Gender, Competitiveness, and Socialization at a Young Age: Evidence from a Matrilineal and a Patriarchal Society. *Review of Economics and Statistics*, 95(4):1438–1443.

Apicella, C. L., Demiral, E. E., and Mollerstrom, J. (2017). No Gender Difference in Willingness to Compete When Competing against Self. *American Economic Review*, 107(5):136–140.

Apicella, C. L. and Dreber, A. (2015). Sex Differences in Competitiveness: Hunter-Gatherer Women and Girls Compete Less in Gender-Neutral and Male-Centric Tasks. *Adaptive Human Behavior and Physiology*, 1(3):247–269.

Balafoutas, L., Kerschbamer, R., and Sutter, M. (2012). Distributional preferences and competitive behavior. *Journal of Economic Behavior & Organization*, 83(1):125–135.

Balafoutas, L. and Sutter, M. (2012). Affirmative action policies promote women and do not harm efficiency in the laboratory. *Science*, 335(6068):579–82.

Banerjee, R., Gupta, N. D., and Villeval, M. C. (2018). The spillover effects of affirmative action on competitiveness and unethical behavior. *European Economic Review*, 101:567–604.

Berge, L. I. O., Bjorvatn, K., Garcia Pires, A. J., and Tungodden, B. (2015). Competitive in the lab, successful in the field? *Journal of Economic Behavior & Organization*, 118:303–317.

Berlin, N. and Dargnies, M.-P. (2016). Gender differences in reactions to feedback and willingness to compete. *Journal of Economic Behavior & Organization*, 130:320–336.

Bönte, W., Lombardo, S., and Urbig, D. (2017). Economics meets psychology: Experimental and self-reported measures of individual competitiveness. *Personality and Individual Differences*, 116:179–185.

Brandts, J., Groenert, V., and Rott, C. (2015). The Impact of Advice on Women's and Men's Selection into Competition. *Management Science*, 61(5):1018–1035.

Buser, T., Cappelen, A., Gneezy, U., Hoffman, M., and Tungodden, B. (2021a). Competitiveness, gender and handedness. *Economics & Human Biology*, 43:101037.

Buser, T., Dreber, A., and Mollerstrom, J. (2017a). The impact of stress on tournament entry. *Experimental Economics*, 20(2):506–530.

Buser, T., Gerhards, L., and van der Weele, J. (2018). Responsiveness to feedback as a personal trait. *Journal of Risk and Uncertainty*, 56(2):165–192.

Buser, T., Niederle, M., and Oosterbeek, H. (2014). Gender, Competitiveness, and Career Choices. *The Quarterly Journal of Economics*, 129(3):1409–1447.

Buser, T., Niederle, M., and Oosterbeek, H. (2020). Can competitiveness predict education and labor market outcomes? Evidence from incentivized choice and survey measures. Working paper, Univeristy of Amsterdam.

Buser, T., Peter, N., and Wolter, S. C. (2017b). Gender, Competitiveness, and Study Choices in High School: Evidence from Switzerland. *American Economic Review*, 107(5):125–130.

Buser, T., Peter, N., and Wolter, S. C. (2022). Willingness to compete, gender and career choices along the whole ability distribution. *Experimental Economics*, 25:1299–1326.

Buser, T., Ranehill, E., and van Veldhuizen, R. (2021b). Gender differences in willingness to compete: The role of public observability. *Journal of Economic Psychology*, 83:102366.

Cadsby, C. B., Servátka, M., and Song, F. (2013). How competitive are female professionals? A tale of identity conflict. *Journal of Economic Behavior & Organization*, 92:284–303.

Cárdenas, J.-C., Dreber, A., von Essen, E., and Ranehill, E. (2012). Gender differences in competitiveness and risk taking: Comparing children in Colombia and Sweden. *Journal of Economic Behavior & Organization*, 83(1):11–23.

Cassar, A., Wordofa, F., and Zhang, Y. J. (2016). Competing for the benefit of offspring eliminates the gender gap in competitiveness. *Proceedings of the National Academy of Sciences*, 113(19):5201–5205.

Chapman, J., Snowberg, E., Wang, S., and Camerer, C. (2019). Loss Attitudes in the U.S. Population: Evidence from Dynamically Optimized Sequential Experimentation (DOSE).

Crosetto, P. and Filippin, A. (2013). The "bomb" risk elicitation task. *Journal of Risk and Uncertainty*, 47(1):31–65.

Danz, D., Vesterlund, L., and Wilson, A. J. (2022). Belief Elicitation and Behavioral Incentive Compatibility. *American Economic Review*, 112(9):2851–2883.

Dargnies, M.-P. (2012). Men Too Sometimes Shy Away from Competition: The Case of Team Competition. *Management Science*, 58(11):1982–2000.

Dariel, A., Kephart, C., Nikiforakis, N., and Zenker, C. (2017). Emirati women do not shy away from competition: Evidence from a patriarchal society in transition. *Journal of the Economic Science Association*, 3(2):121–136.

Dariel, A. and Nikiforakis, N. (2022). Is there a motherhood gap in the willingness to compete for pay? Working paper, NYU Abu DHabi.

Datta Gupta, N., Poulsen, A., and Villeval, M.-C. (2013). Gender matching and competitiveness: Experimental evidence. *Economic Inquiry*, 51(1):816–835.

Dechenaux, E., Kovenock, D., and Sheremeta, R. M. (2015). A survey of experimental research on contests, all-pay auctions and tournaments. *Experimental Economics*, 18(4):609–669.

Dohmen, T. and Falk, A. (2011). Performance Pay and Multidimensional Sorting: Productivity, Preferences, and Gender. *American Economic Review*, 101(2):556–590.

Dreber, A., von Essen, E., and Ranehill, E. (2014). Gender and competition in adolescence: Task matters. *Experimental Economics*, 17(1):154–172.

Eckel, C. C. and Grossman, P. J. (2002). Sex differences and statistical stereotyping in attitudes toward financial risk. *Evolution and Human Behavior*, 23:281–295.

Fallucchi, F., Nosenzo, D., and Reuben, E. (2020). Measuring preferences for competition with experimentally-validated survey questions. *Journal of Economic Behavior & Organization*, 178:402–423.

Fischbacher, U. (2007). Z-Tree: Zurich toolbox for ready-made economic experiments. *Experimental Economics*, 10(2):171–178.

Gächter, S. and Renner, E. (2010). The effects of (incentivized) belief elicitation in public goods experiments. *Experimental Economics*, 13(3):364–377.

Geraldes, D. (2020). Women Dislike Competing Against Men. Working Paper 3741649, SSRN.

Gillen, B., Snowberg, E., and Yariv, L. (2019). Experimenting with Measurement Error: Techniques with Applications to the Caltech Cohort Study. *Journal of Political Economy*, 127(4):1826–1863.

Gneezy, U., Leonard, K. L., and List, J. A. (2009). Gender Differences in Competition: Evidence From a Matrilineal and a Patriarchal Society. *Econometrica*, 77(5):1637–1664.

Greiner, B. (2015). Subject pool recruitment procedures: Organizing experiments with ORSEE. *Journal of the Economic Science Association*, 1(1):114–125.

Halko, M.-L. and Sääksvuori, L. (2017). Competitive behavior, stress, and gender. *Journal of Economic Behavior & Organization*, 141:96–109.

Harrison, G. W. and Phillips, R. D. (2014). Subjective Beliefs and Statistical Forecasts of Financial Risks: The Chief Risk Officer Project. In Andersen, T. J., editor, *Contemporary Challenges in Risk Management*, pages 163–202. Palgrave Macmillan UK, London.

Healy, A. and Pate, J. (2011). Can Teams Help to Close the Gender Competition Gap? *The Economic Journal*, 121(555):1192–1204.

Heckman, J., Jagelka, T., and Kautz, T. (2019). Some Contributions of Economics to the Study of Personality. Technical Report w26459, National Bureau of Economic Research, Cambridge, MA.

Holt, C. A. and Laury, S. K. (2002). Risk Aversion and Incentive Effects. *American Economic Review*, 92(5):1644–1655.

Hossain, T. and Okui, R. (2013). The Binarized Scoring Rule. *The Review of Economic Studies*, 80(3):984–1001.

Ifcher, J. and Zarghamee, H. (2016). Pricing competition: A new laboratory measure of gender differences in the willingness to compete. *Experimental Economics*, 19(3):642–662.

Jung, S. and Vranceanu, R. (2019). Willingness to compete: Between- and within-gender comparisons. *Managerial and Decision Economics*, page mde.3004.

Kamas, L. and Preston, A. (2012). The importance of being confident; gender, career choice, and willingness to compete. *Journal of Economic Behavior & Organization*, 83(1):82–97.

Kamas, L. and Preston, A. (2018). Competing with confidence: The ticket to labor market success for college-educated women. *Journal of Economic Behavior & Organization*, 155:231–252.

Karni, E. (2009). A Mechanism for Eliciting Probabilities. *Econometrica*, 77(2):603–606.

Khachatryan, K., Dreber, A., von Essen, E., and Ranehill, E. (2015). Gender and preferences at a young age: Evidence from Armenia. *Journal of Economic Behavior & Organization*, 118:318–332.

Lee, S., Niederle, M., and Kang, N. (2014). Do single-sex schools make girls more competitive? *Economics Letters*, 124(3):474–477.

Lim, W., Matros, A., and Turocy, T. L. (2014). Bounded rationality and group size in Tullock contests: Experimental evidence. *Journal of Economic Behavior & Organization*, 99:155–167.

Lozano, L., Ranehill, E., and Reuben, E. (2023). Gender and Preferences in the Labor Market: Insights from Experiments. In Zimmermann, K. F., editor, *Handbook of Labor, Human Resources and Population Economics*. Springer.

Mayr, U., Wozniak, D., Davidson, C., Kuhns, D., and Harbaugh, W. T. (2012). Competitiveness across the life span: The feisty fifties. *Psychology and Aging*, 27(2):278–285.

Morgan, J., Orzen, H., and Sefton, M. (2012). Endogenous entry in contests. *Economic Theory*, 51:435–463.

Muller, J. and Schwieren, C. (2012). Can Personality Explain what is Underlying Women's Unwillingness to Compete? *Journal of Economic Psychology*, 33:448–460.

Niederle, M. (2017). A Gender Agenda: A Progress Report on Competitiveness. *American Economic Review*, 107(5):115–119.

Niederle, M., Segal, C., and Vesterlund, L. (2013). How Costly Is Diversity? Affirmative Action in Light of Gender Differences in Competitiveness. *Management Science*, 59(1):1–16.

Niederle, M. and Vesterlund, L. (2007). Do Women Shy Away From Competition? Do Men Compete Too Much? *The Quarterly Journal of Economics*, 122(3):1067–1101.

Niederle, M. and Vesterlund, L. (2011). Gender and Competition. *Annual Review of Economics*, 3(1):601–630.

Petrie, R. and Segal, C. (2017). Gender differences in competitiveness: The role of prizes. Working paper, Texas A&M University.

Price, C. R. (2012). Gender, Competition, and Managerial Decisions. *Management Science*, 58(1):114–122.

Reuben, E., Sapienza, P., and Zingales, L. (2019). *Taste for Competition and the Gender Gap among Young Business Professionals*. PhD thesis, Working paper, New York University Abu Dhabi.

Reuben, E., Wiswall, M., and Zafar, B. (2017). Preferences and Biases in Educational Choices and Labour Market Expectations: Shrinking the Black Box of Gender. *The Economic Journal*, 127(604):2153–2186.

Saccardo, S., Pietrasz, A., and Gneezy, U. (2018). On the Size of the Gender Difference in Competitiveness. *Management Science*, 64(4):1541–1554.

Samak, A. C. (2013). Is there a gender gap in preschoolers' competitiveness? An experiment in the U.S. *Journal of Economic Behavior & Organization*, 92:22–31.

Sheremeta, R. M. (2011). Contest design: An experimental investigation. *Economic Inquiry*, 49(2):573–590.

Shurchkov, O. (2012). Under Pressure: Gender Differences in Output Quality and Quantity Under Competition and Time Constraints. *Journal of the European Economic Association*, 10(5):1189–1213.

Sutter, M. and Glätzle-Rützler, D. (2015). Gender Differences in the Willingness to Compete Emerge Early in Life and Persist. *Management Science*, 61(10):2339–2354.

Sutter, M., Glätzle-Rützler, D., Balafoutas, L., and Czermak, S. (2016). Cancelling out early age gender differences in competition: An analysis of policy interventions. *Experimental Economics*, 19(2):412–432.

Toubia, O., Johnson, E., Evgeniou, T., and Delquié, P. (2013). Dynamic Experiments for Estimating Preferences: An Adaptive Method of Eliciting Time and Risk Parameters. *Management Science*, 59(3):613–640.

Trautmann, S. T. and van de Kuilen, G. (2015). Belief Elicitation: A Horse Race among Truth Serums. *The Economic Journal*, 125(589):2116–2135.

van de Kuilen, G. and Wakker, P. P. (2011). The Midweight Method to Measure Attitudes Toward Risk and Ambiguity. *Management Science*, 57(3):582–598.

van Veldhuizen, R. (2022). Gender Differences in Tournament Choices: Risk Preferences, Overconfidence or Competitiveness? *Journal of the European Economic Association*, page jvac031.

Wang, S. W. (2011). Incentive effects: The case of belief elicitation from individuals in groups. *Economics Letters*, 111(1):30–33.

Wozniak, D., Harbaugh, W. T., and Mayr, U. (2014). The Menstrual Cycle and Performance Feedback Alter Gender Differences in Competitive Choices. *Journal of Labor Economics*, 32(1):161–198.

Zhang, Y. J. (2019). Culture, Institutions and the Gender Gap in Competitive Inclination: Evidence from the Communist Experiment in China. *The Economic Journal*, 129(617):509–552.

Zhong, S., Shalev, I., Koh, D., Ebstein, R. P., and Chew, S. H. (2018). Competitiveness and stress. *International Economic Review*, 59(3):1263–1281.

Appendix

A.1 Summary of papers measuring preferences for competition

Table A.1 lists papers studying preferences for competition using slight variations of the Niederle and Vesterlund (2007) experimental design. This list is based on the papers reviewed by Dariel et al. (2017) plus a few more papers that share design choices with our experiment. The first two columns of the table indicate how the decision to compete is implemented: either as a single binary choice between individual and competitive pay or a more continuous measure of this choice using a multiple price list or a slider. The next six columns correspond to the belief elicitation task. Columns three through six describe the belief elicitation task. Most papers elicit the participants' expected rank within their group or the probability of being the group's winner. Other methods include eliciting the expected number of correct sums, self-reported assessments of their relative performance, and the expected number of sums performed by men and women. The seventh column indicates whether beliefs are elicited before or after the payment-scheme choice. The eighth column indicates whether the beliefs are incentivized, and the ninth column further specifies if the incentivization is done using the binarized scoring rule. Finally, the last three columns indicate whether risk preferences are measured with an unincentivized survey question (tenth column), incentivized lotteries in a multiple price list (eleventh column), or another incentivized method (twelfth column).

A.2 Additional details of the experimental design

High and low payments in Part 2

In Table A2, we list the high π^H and low π^L amounts used in the five decision sets used to measure the participants' preferences for competition. Each decision set corresponds to a MPL where participants choose between individual and competitive pay. The order in which the decisions sets appear to a participant is randomized.

Table A2. High and low values the five decision sets (in euros)

	Decision set				
	1	2	3	4	5
Group size three					
π^H	4.00	6.00	1.50	4.00	2.00
π^L	0.00	0.00	0.00	1.00	0.50
Group size six					
π^H	6.00	9.00	3.00	4.00	3.50
π^L	0.00	0.00	0.00	1.00	0.50

Table A1. List of studies using the Niederle and Vesterlund (2007) and their respective methods

	Payment-scheme choice		Belief elicitation task						Risk elicitation task		
			Statistic			Placement	Incentivized				
Study	*Binary*	*MPL / slider*	*Rank*	*Prob. win*	*Other*	*Before / after*	*Yes / no*	*BSR*	*Survey*	*MPL*	*Other*
Niederle and Vesterlund (2007)	✓	×	✓	×	×	after	✓	×	×	×	✓
Gneezy et al. (2009)	✓	×	×	×	×	×	×	×	×	×	✓
Healy and Pate (2011)	✓	×	✓	×	×	after	✓	×	×	×	✓
Balafoutas and Sutter (2012)	✓	×	✓	×	×	after	✓	×	×	×	×
Balafoutas et al. (2012)	✓	×	✓	×	×	after	✓	×	×	✓	×
Cárdenas et al. (2012)	✓	×	×	×	✓	after	×	×	×	✓	×
Dargnies (2012)	✓	×	×	×	✓	after	×	×	×	×	✓
Kamas and Preston (2012)	✓	×	✓	×	✓	after	✓	×	✓	✓	×
Mayr et al. (2012)	✓	×	✓	×	×	before	✓	×	×	×	×
Muller and Schwieren (2012)	✓	×	✓	×	×	after	×	×	×	✓	×
Price (2012)	✓	×	✓	×	×	after	✓	×	×	×	×
Shurchkov (2012)	✓	×	✓	×	✓	after	×	×	×	×	×
Andersen et al. (2013)	✓	×	×	×	×	×	×	×	×	×	×
Cadsby et al. (2013)	✓	×	✓	×	×	after	✓	×	×	×	✓
Datta Gupta et al. (2013)	✓	×	×	×	✓	after	✓	×	✓	×	×
Niederle et al. (2013)	✓	×	✓	×	×	after	✓	×	×	×	✓
Samak (2013)	✓	×	×	×	✓	after	×	×	×	×	×
Buser et al. (2014)	✓	×	×	×	✓	after	×	×	✓	×	×
Dreber et al. (2014)	✓	×	✓	×	×	after	×	×	×	✓	×
Lee et al. (2014)	✓	×	×	×	✓	after	×	×	×	×	✓
Wozniak et al. (2014)	✓	×	×	×	✓	after	✓	×	×	✓	×
Apicella and Dreber (2015)	✓	×	×	×	×	×	×	×	×	×	×
Brandts et al. (2015)	✓	×	×	×	✓	after	✓	×	×	×	✓
Khachatryan et al. (2015)	✓	×	✓	×	×	after	×	×	×	✓	×
Sutter and Glätzle-Rützler (2015)	✓	×	✓	×	×	after	×	×	×	×	×
Almås et al. (2016)	✓	×	✓	×	×	before	×	×	✓	✓	×

Continuation Table A1. List of studies using the Niederle and Vesterlund (2007) and their respective methods

	Payment-scheme choice		Belief elicitation task						Risk elicitation task		
			Statistic			Placement	Incentivized				
Study	*Binary*	*MPL / slider*	*Rank*	*Prob. win*	*Other*	*Before / after*	*Yes / no*	*BSR*	*Survey*	*MPL*	*Other*
Berlin and Dargnies (2016)	✓	×	×	✓	×	before	✓	✓	×	×	✓
Cassar et al. (2016)	✓	×	×	×	✓	after	×	×	×	✓	×
Ifcher and Zarghamee (2016)	×	✓	✓	×	×	after	✓	×	×	✓	✓
Sutter et al. (2016)	✓	×	✓	×	×	after	✓	×	×	×	×
Apicella et al. (2017)	✓	×	×	×	✓	after	✓	×	✓	×	×
Buser et al. (2017b)	✓	×	×	×	×	×	×	×	×	✓	×
Buser et al. (2017a)	✓	×	×	✓	×	after	×	×	✓	×	×
Bönte et al. (2017)	✓	×	✓	×	✓	after	×	×	✓	×	×
Dariel et al. (2017)	✓	×	×	×	✓	after	×	×	✓	×	×
Halko and Sääksvuori (2017)	✓	×	✓	×	×	after	✓	×	✓	✓	×
Petrie and Segal (2017)	×	✓	×	✓	×	after	✓	✓	×	×	✓
Reuben et al. (2017)	✓	×	✓	✓	×	after	✓	✓	×	✓	×
Banerjee et al. (2018)	✓	×	✓	✓	✓	after	✓	✓	×	✓	×
Buser et al. (2018)	✓	×	✓	×	×	after	✓	×	✓	×	×
Saccardo et al. (2018)	×	✓	×	✓	✓	after	×	×	✓	✓	×
Zhong et al. (2018)	✓	×	✓	×	×	after	✓	×	×	✓	×
Jung and Vranceanu (2019)	×	✓	✓	×	×	after	✓	×	✓	×	✓
Reuben et al. (2019)	✓	×	✓	×	×	after	✓	×	×	✓	×
Zhang (2019)	✓	×	✓	×	×	after	×	×	×	×	✓
Fallucchi et al. (2020)	×	✓	×	✓	×	after	✓	✓	✓	✓	×
Geraldes (2020)	✓	×	✓	×	×	after	✓	✓	✓	×	×
Buser et al. (2021b)	✓	×	✓	×	×	after	✓	×	×	×	✓
Buser et al. (2021a)	✓	×	×	×	✓	before	×	×	✓	×	×
van Veldhuizen (2022)	✓	×	×	✓	×	before	✓	✓	✓	✓	×
Danz et al. (2022)	✓	×	×	✓	×	after	✓	✓	×	×	✓

Probabilities used in the multiple price lists

We use the procedure described below to have MPLs with a reasonable degree of accuracy (i.e., the steps between items are not too large) and ensure that the participants belief of being their group's winner is contained within the MPL.

Each multiple price list consists of ten rows $r \in [1, 10]$. Each row has a probability of winning in individual pay $p_r \in [0, 100]$. As one goes down the list, the probability of winning in individual pay increases by z percentage points (i.e., $p_{r+1} = p_r + z$). Hence, in a given MPL, the probabilities range from $p_1 = p_L$ to $p_{10} = p_L + 9z$. For a participant i, we use a reference probability $b_i \in [0, 100]$ to set the starting probability, p_L for i's MPLs in the following way:

- If $b_i \leq 9z$ then $p_L = 0$.
- If $b_i \geq 1 - 9z$ then $p_L = 1 - 9z$.
- If $9z < b_i < 1 - 9z$ then $p_L = b_i - 5z + \epsilon$, where ϵ is a random number drawn from a uniform distribution with support $[-0.025, 0.025]$.

The values of z varied across the various decision sets as follows: $z = 2$ in decision set 1, $z = 1$ in decision set 2, $z = 3$ in decision set 3, $z = 2$ ($z = 3$) in decision set 4 for group sizes of three (six), and $z = 4$ in decision set 5. We varied the values of z and introduced the random component ϵ so that participants would not see the same probability range in every decision set.

The reference probability b_i depends on when participants' beliefs are elicited. In the *Belief-first* treatment, b_i equaled the participants' elicited belief of being their group's winner. In the *Choice-first* treatment, b_i is obtained by giving participants two additional MPLs designed to narrow down the range of probabilities where a participant switches from competitive to individual pay. In the first additional MPL $p_L = 0.05$ and $z = 0.10$. We construct the second additional MPL based on the answers to the first additional MPL. Specifically, participants who switch from competitive pay to individual pay at a probability $p_r \leq 0.35$ get $p_L = 0.05$, those who switch at a probability $0.35 < p_r < 0.65$ get $p_L = 0.30$, and those who switch at a probability $p_r \geq 0.65$ get $p_L = 0.50$. In all cases $z = 0.05$. We then set b_i as the probability at which the participant switches from competitive to individual pay in the second additional MPL.[22]

A.3 Descriptive statistics of the adding task

Table A3 displays the mean and standard deviation for the number of correct sums in the adding task, the reported belief of being the group's winner, and overconfidence calculated as

[22]For participants that switch multiple times or switch from individual to competitive pay, the switching probabilities equaled the number of competitive pay choices multiplied by z plus p_L.

the difference between their belief and the probability of being the winner of a randomly-formed group. Descriptive statistics are shown for the pooled data and also depending on group size, the timing of belief elicitation, the order in which the task was played, and gender.

Table A3. Descriptive statistics for performance and beliefs in the adding task

Note: Mean and standard deviations (in parenthesis) for the number of correct sums in the adding task, the participants' mean belief of being their group's winner (in percent), and the participants' mean overconfidence (belief of winning minus their probability of winning, in percent). Statistics are presented by group size, the timing of the belief elicitation task, whether the task is played first or second, and gender.

		Correct sums	**Belief of winning**	**Over-confidence**
Pooled data		11.4 (4.7)	44.9 (26.1)	19.9 (27.1)
By group size	Group size three	11.4 (4.7)	53.8 (22.3)	20.4 (25.7)
	Group size six	11.3 (4.7)	36.0 (26.7)	19.4 (28.4)
By timing of beliefs	Beliefs first	10.9 (4.6)	42.6 (26.2)	19.7 (27.3)
	Choices first	11.7 (4.7)	47.0 (26.0)	20.1 (26.9)
By order of play	Played first	10.8 (4.4)	42.0 (25.6)	20.2 (26.9)
	Played second	11.9 (4.9)	47.8 (26.4)	19.6 (27.3)
By gender	Men	12.2 (5.2)	48.3 (27.5)	17.7 (27.9)
	Women	10.8 (4.2)	42.6 (25.0)	21.4 (26.4)

A.4 Mean willingness to pay to compete

In this subsection, we show the distribution of the participants' willingness to pay to compete when it is calculated using the mean value of the five ω_{it}s instead of the median. We graph the distribution of this variable in Figure A1.

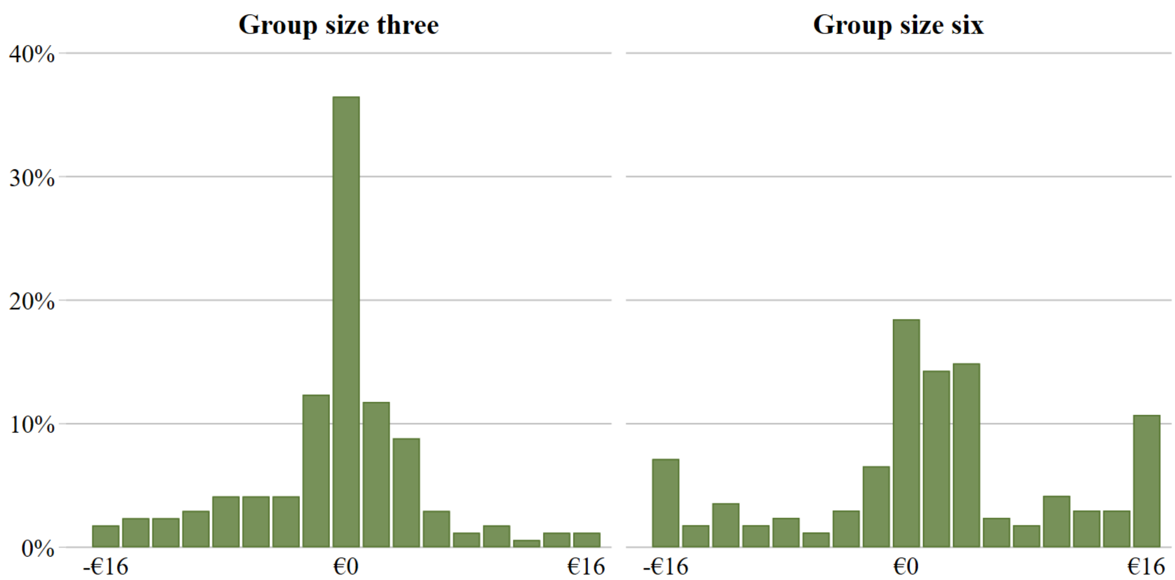


Figure A1. Distribution of participants' willingness to pay to compete calculated using the average value of ω_{it} across the five sets

Note: For visual ease, Figure A1 censors values at −16 and 16. The percentage of participants that fall outside this range is 2% in groups of three (4 out of 170 participants) and 17% for groups of six (28 out of 168 participants).

A.5 Supplementary analysis: subcategories

Switching behavior

In this subsection, we present the results for consistency of switching behavior displayed in Tables 3 and 2 when we divide the sample into different subcategories as a robustness check. Specifically, we divide our sample into three subcategories: (i) the order in which participants played the experimental tasks, (ii) the timing of the belief elicitation task, and (iii) gender.

Table A4 shows whether behavior within sets is consistent with utility maximization for the various subcategories. Behavior within decision sets is *inconsistent* if there are multiple switches or a unique non-monotonic switch. Similarly, behavior within decision sets as *consistent* if there is one switch from competitive to individual pay (single switch) or if all choices correspond to either competitive or individual pay (no switch). The table shows that switching behavior within subcategories is generally consistent with that observed in the main analysis. Overall, participants in all subcategories switched consistently in at least 94% of all decision sets. By and large, switching behavior across subcategories is similar. The one noticeable difference is that participants in the *Belief-first* treatment are more likely to have sets with no switching and less likely to have sets with a single switch than those in *Choice-first*.

Table A4. Consistency in switching behavior within decision sets

Note: Fraction of decision sets with inconsistent behavior: with either *multiple switches* or a single *non-monotonic switch* from individual to competitive pay. Fraction of decision sets with consistent behavior with either a *single switch* from competitive to individual pay or *no switch*.

	Inconsistent Behavior				**Consistent Behavior**			
	Multiple switches		*Non-monotonic switch*		*Single switch*		*No switch*	
Group size	Three	Six	Three	Six	Three	Six	Three	Six
Pooled data	3.1%	3.9%	1.0%	0.7%	77.0%	76.0%	18.9%	19.4%
By order of play:								
Played first	3.6%	2.6%	2.7%	2.11%	76.9%	78.1%	16.7%	17.2%
Played second	0.9%	2.4%	1.1%	2.2%	77.0%	73.8%	21.1%	21.6%
By timing of beliefs:								
Beliefs first	3.9%	3.7%	2.2%	1.9%	67.9%	68.2%	25.9%	26.2%
Choices first	0.7%	1.4%	1.5%	2.4%	85.3%	83.1%	12.5%	13.2%
By gender:								
Men	2.4%	2.64%	0.2%	1.3%	74.7%	75.2%	22.6%	20.9%
Women	2.9%	3.0%	2.3%	2.1%	78.5%	76.5%	16.4%	18.4%

Table A5 shows participants' switching behavior across the five decision sets for the different subcategories. The table shows the fraction of participants with: inconsistent switching behavior in at least one decision set (column I), consistent behavior in all five decision sets (column II), consistent behavior in all five decision sets and a single consistent switch in a majority of decision sets (column III), and consistent behavior in all five decision sets and a single consistent switch in all five decision sets (column IV).

Table A5. Consistency in switching behavior within individuals

Note: (I) Fraction of participants with inconsistent switching behavior in at least one decision set. (II) Fraction of participants with consistent behavior in all five decision sets. (III) Fraction of participants with consistent behavior in all five decision sets and a single consistent switch in a majority of decision sets (three or more). (IV) Fraction of participants with consistent behavior in all five decision sets and a single consistent switch in all five decision sets.

	Inconsistent Behavior		**Consistent Behavior**					
	I		II		III		IV	
Group size	Three	Six	Three	Six	Three	Six	Three	Six
Pooled data	8.9%	11.6%	91.1%	88.4%	75.9%	75.0%	54.5%	45.5%
By order of play:								
Played first	11.8%	11.4%	88.2%	88.6%	79.1%	78.1%	52.7%	49.1%
Played second	6.1%	11.8%	93.9%	88.2%	72.8%	71.8%	56.1%	41.8%
By timing of beliefs:								
Beliefs first	10.3%	13.1%	89.7%	86.9%	64.5%	66.5%	48.6%	41.1%
Choices first	7.7%	10.3%	92.3%	89.7%	86.3%	82.9%	59.8%	49.6%
By gender:								
Men	6.6%	9.9%	93.4%	90.1%	73.6%	75.8%	49.5%	46.2%
Women	10.5%	12.8%	89.5%	87.2%	77.4%	74.4%	57.9%	45.1%

Overall, over 86% of participants switch consistently in all five decision sets in all subcategories. Moreover, in all subcategories, a majority of participants switch once from competitive to individual pay in a majority of sets. Once again, the only evident difference within subcategories is that participants in the *Belief-first* treatment are more likely to have a single consistent switch in a majority of decision sets than participants in *Choice-first*.

Willingness to pay to compete

In this subsection, we present the results concerning the participants' willingness to pay to compete for the various subcategories. In addition, we also show the results when we include participants who were excluded in the main analysis. First, we redo the analysis including participants who switched consistently in all five sets but had three or more sets with no switching. Second, we redo the analysis including all participants and decision sets. In sets with multiple switches, the value of ω_{it} is calculated based on the first switch from competitive to individual pay. In sets with a single non-monotonic switch, the value of ω_{it} is the largest value in the set.

Table A6 shows the mean and standard deviation for $\bar{\omega}i$ for the pooled data and the different subcategories. In all subcategories, the participants' willingness to pay to compete has a lower mean and a smaller standard deviation in groups of three compared to groups of six.

Table A6. Descriptive statistics of the participants' willingness to pay to compete ($\bar{\omega}_i$)

Note: Mean, standard deviations and sample size for participants willingness to compete ($\bar{\omega}_i$) by group size. Statistics are presented by whether the task is played for the first or second time, the timing of the belief elicitation task, gender and inclusion of sets with no or inconsistent switch.

	Group size three			**Group size six**		
	mean	*s.d.*	*n*	*mean*	*s.d.*	*n*
Pooled data	-0.65	5.46	170	1.22	8.66	168
By order of play:						
Played first	-0.26	5.31	87	1.29	8.68	89
Played second	-1.06	5.63	83	1.13	8.69	79
By timing of beliefs:						
Beliefs first	0.18	1.12	69	1.49	2.73	71
Choices first	-1.21	6.99	101	1.01	11.17	97
By gender:						
Men	-1.54	5.25	67	1.17	9.10	69
Women	-0.07	5.55	103	1.25	8.38	99
Including more cases:						
Including sets without switch	-0.62	5.38	204	1.35	8.44	198
Including inconsistent sets	-0.70	5.32	224	1.25	8.46	224

Table A7 displays the percentage of participants who are persistently competition loving, persistently competition averse, and 'not defined' for the various subcategories. In most subcategories, a clear majority (around 70%) of participants are either persistently competition loving or persistently competition averse. The only exception are participants in the *Beliefs-first* treatment, where around half of the participants are classified as 'not defined.' However, note that, even in this subcategory, the distribution of participants classified as persistently competition loving or persistently competition averse is different from a benchmark distribution where participants do not have preferences for competition.

Table A7. Persistently competition-loving or competition-averse participants

Note: Percentage of participants who are persistently competition loving ('loving'), defined as switching at rows above r^*_{it} in at least 4 out of 5 sets, or competition averse ('averse'), switching at rows below r^*_{it} in at least 4 out of 5 sets, where r^*_{it} is the highest row where a participant's belief of being the group's winner exceeds the probability of getting the high amount in individual pay. The remaining participants are classified as 'not defined'. 170 participants for groups of three and 168 for groups of six.

	Group size three			**Group size six**		
	Loving	Averse	Not defined	Loving	Averse	Not defined
Pooled data	36.7%	34.7%	28.8%	51.1%	23.2%	25.6%
By order of play:						
Played first	37.9%	33.3%	28.7%	51.7%	24.7%	23.6%
Played second	34.5%	36.1%	28.9%	50.6%	21.5%	27.9%
By timing of beliefs:						
Beliefs first	28.9%	15.9%	55.1%	43.7%	8.5%	47.9%
Choices first	41.6%	47.5%	10.9%	56.7%	34.0%	9.3%
By gender:						
Men	29.9%	41.8%	28.4%	46.4%	21.7%	31.9%
Women	40.8%	30.1%	29.1%	54.6%	24.2%	21.2%
Including more cases:						
Including sets without switch	36.3%	35.8%	27.9%	54.0%	23.7%	22.2%
Including inconsistent sets	37.9%	33.5%	28.6%	54.0%	22.3%	23.7%

A.6 Instructions

Below are the instructions for the *before* treatment with first a group size of three followed by a group size of six. Instructions for the other treatments are very similar and available upon request.

General Instructions

Welcome to the experiment. In the experiment today, you will be asked to complete five tasks. Before each task, you will receive detailed instructions and description of how your earnings in that task are determined.

Your total earnings at the end of the experiment are the sum of the following two components:

1. A €10 show-up fee.

2. Your earnings in one of the five tasks. Specifically, at the end of the experiment, one of the five tasks you will complete during the experiment will be randomly chosen for payment purposes.

During the experiment, the use of cell phones is prohibited. All your information, decisions, and performance during this experiment are anonymous.

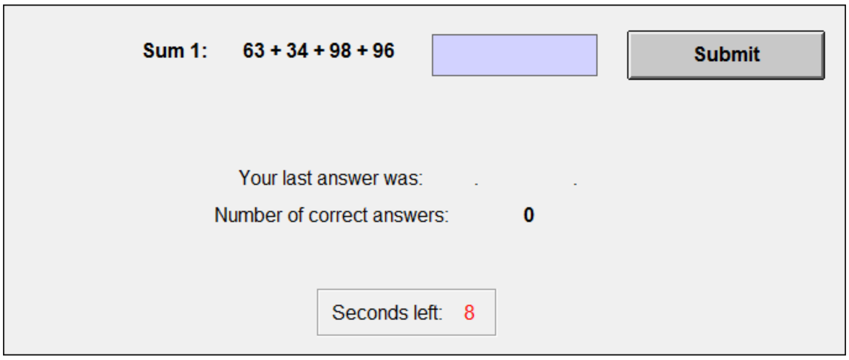
If you have a question, please raise your hand. An experimenter will come and answer your question in private.

Now you will start Task 1, please read the instructions of Task 1 carefully.

Task 1

In Task 1, you will be randomly assigned to a group of three participants. In other words, you will be matched with two other participants in the room.

In Task 1 you will be given four minutes to calculate a series of sums of four two-digit numbers (see the screenshot below). You cannot use a calculator, but you are welcome to use the provided scratch paper. You submit an answer by clicking the button "Next". When you submit an answer, the computer will immediately tell you whether the answer is correct or incorrect and a new sum is generated.



Your earnings in Task 1 depend on your number of correct sums. Specifically, you can earn either a high amount or a low amount per correct sum. The high amount will vary between €1.5 and €6 per correct sum, and the low amount will vary between €0 and €1. You will be given the precise values before you perform the task. Whether you are paid a high amount or a low amount depends on your choices. Before you perform the task, you will choose between **individual pay** and **competitive pay**. The two payments schemes are as follows:

- **Individual pay:** if you choose individual pay, whether you receive a high or low amount per correct sum depends on chance. With individual pay your earnings do NOT depend on the performance of others in your group.

- **Competitive pay:** if you choose competitive pay, whether you receive a high or low amount per correct sum depends on your performance and the performance of the other two members of your group. Specifically, you will be your group's winner if you solve more sums in Task 1 than all others in your group in Task 1. If there are ties, the winner will be randomly determined among the tied group members. If you are your group's winner, you will receive the high amount per correct sum. If you are NOT your group's winner, then you are one of the two losers in the group. If you are one of the group's losers, you will receive the low amount per correct sum.

Practice round: Before Task 1 starts, you will have two minutes to get familiar with the screen and to practice the calculation of series of sums of four two-digit numbers. Please notice that your answers in this practice round will not be considered for your earnings in this experiment.

Once you are done reading, click on the "NEXT" button on your screen.

Task 2

In this task, you can earn money by answering the following question:

"How likely do you think it is that you are the winner of your group in Task 1?"

Your answer can go from 0 (meaning you are completely certain that you are not the winner of your group) to 100 (meaning you are completely certain that you are the winner of your group).

Your earnings in Task 2 can be either **€0 or €20**. The probability of earning €20 depends on two things:

1. The actual outcome (whether you are the winner or a loser in your group)

2. The likelihood you selected as the answer to the question above.

The closer the likelihood you choose is to your actual outcome in Task 1, the higher the probability you have of earning €20. This probability is based on the formulas you see in the footnote.[23] It is not necessary for you to understand precisely the formulas, but it's important that you know that these formulas have been designed so that **your expected earnings are higher the closer your answer is to your actual likelihood of being your group's winner**.

To help you to think about your likelihood of being your group's winner, it is useful to think **how your performance in Task 1 ranks compared to the performance of all participants.** The table provided in the next page displays this information. In the table you can see for each possible rank (from being on the top 0% to being on the top 100%) the likelihood that someone with that rank is the winner of a group of three. The numbers on the table are calculated based on you being randomly assigned to groups of three. For example, imagine that your performance in Task 1 puts you in the Top 10%. This means that you performed better than 90% of all participants in the study and you performed worse than around 10% of all participants in the study. Then for you to be the winner it must be the case that **all two** of the other members of your group have a worse rank than you. In other words,

- You have been randomly matched **only** with participants who **all** come from the 90% of participants who performed worse than you, and

- You have **not** been randomly matched with **any** of the 10% of participants who performed better than you.

The table shows that, for someone in the Top 10%, the likelihood that this happens is 81.00%.

[23]Probability of earning €20 if you are the winner = $1 - (1 - \text{Your selected likelihood}/100)^2$. Probability of earning €20 if you are one of the losers = $1 - (\text{Your selected likelihood}/100)^2$.

Your performance is in the Top ...	The likelihood that you are your group's winner is...
0%	100.00%
1%	98.01%
2%	96.04%
3%	94.09%
4%	92.16%
5%	90.25%
6%	88.36%
7%	86.49%
8%	84.64%
9%	82.81%
10%	81.00%
11%	79.21%
12%	77.44%
13%	75.69%
14%	73.96%
15%	72.25%
16%	70.56%
17%	68.89%
18%	67.24%
19%	65.61%
20%	64.00%
21%	62.41%
22%	60.84%
23%	59.29%
24%	57.76%
25%	56.25%
26%	54.76%
27%	53.29%
28%	51.84%
29%	50.41%
30%	49.00%
31%	47.61%
32%	46.24%
33%	44.89%
34%	43.56%
35%	42.25%
36%	40.96%
37%	39.69%
38%	38.44%
39%	37.21%
40%	36.00%
41%	34.81%
42%	33.64%
43%	32.49%
44%	31.36%
45%	30.25%
46%	29.16%
47%	28.09%
48%	27.04%
49%	26.01%
	continues →

Group size 3

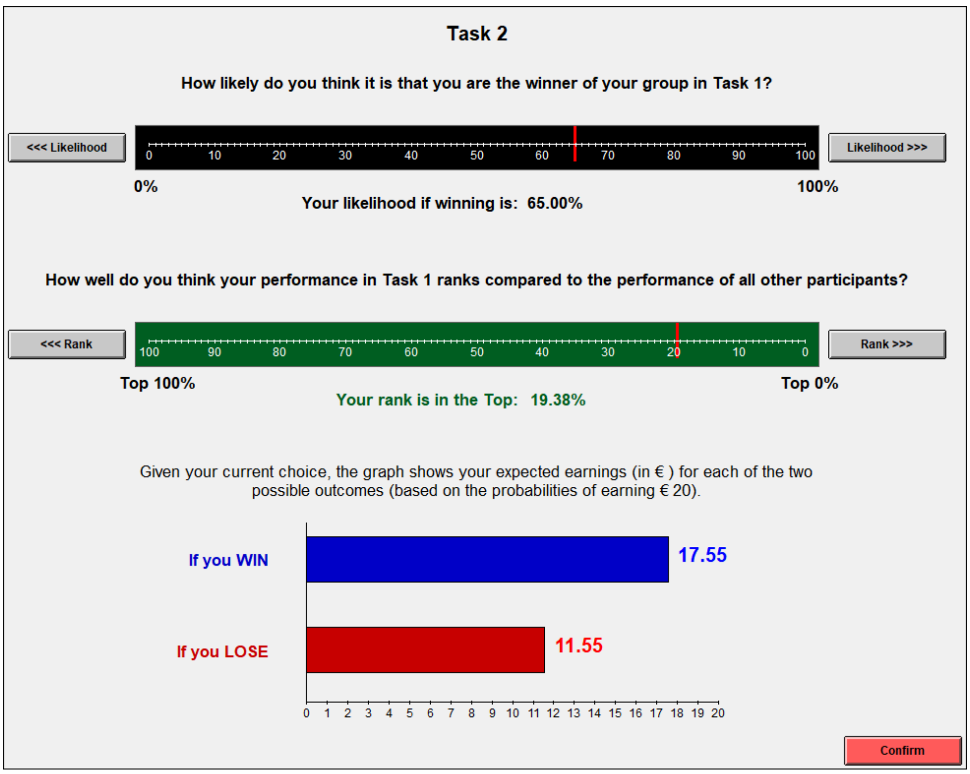
Your performance is in the Top ...	The likelihood that you are your group's winner is...
50%	25.00%
51%	24.01%
52%	23.04%
53%	22.09%
54%	21.16%
55%	20.25%
56%	19.36%
57%	18.49%
58%	17.64%
59%	16.81%
60%	16.00%
61%	15.21%
62%	14.44%
63%	13.69%
64%	12.96%
65%	12.25%
66%	11.56%
67%	10.89%
68%	10.24%
69%	9.61%
70%	9.00%
71%	8.41%
72%	7.84%
73%	7.29%
74%	6.76%
75%	6.25%
76%	5.76%
77%	5.29%
78%	4.84%
79%	4.41%
80%	4.00%
81%	3.61%
82%	3.24%
83%	2.89%
84%	2.56%
85%	2.25%
86%	1.96%
87%	1.69%
88%	1.44%
89%	1.21%
90%	1.00%
91%	0.81%
92%	0.64%
93%	0.49%
94%	0.36%
95%	0.25%
96%	0.16%
97%	0.09%
98%	0.04%
99%	0.01%
100%	0.00%

You will indicate your likelihood of being your group's winner in a screen like the one below. As you can see, there are two sliders in the top part of the screen. You can select your answer by moving the cursors in these two different sliders:

- **In the black slider**, you can select your likelihood of being the winner of your group. Your answer can go from 0% (meaning you are completely certain that you are not the winner of your group) to 100% (meaning you are completely certain that you are the winner of your group).
- **In the green slider**, you can select how your performance in task 1 ranks compared to the performance of all participants. Your answer can go from Top 100% (you performed worse than **all** other participants of the study) to Top 0% (you performed better than ALL other participants in the study).

Please notice that the information displayed in both sliders is always consistent with each other. In other words, when you select a likelihood on the black slider, the cursor on the green slider will automatically mark the rank associated with your selected likelihood. Similarly, when you select a rank on the green slider, the cursor on the black slider will automatically mark the likelihood associated with your selected rank. The values of the sliders are based on the numbers you can see in the table of the previous page.

The cursors will appear on the sliders only after you have clicked on one of the sliders for the first time.



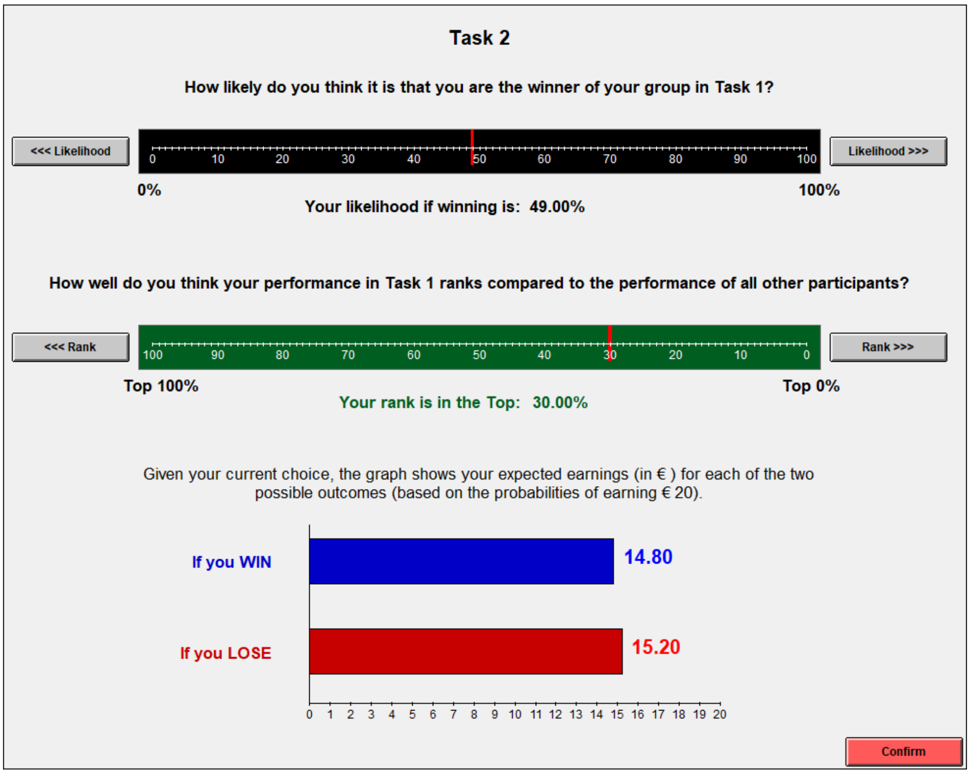
To help you to understand the consequences of your choice, below the sliders, you will also see the **expected earnings** associated to your choice in the two possible outcomes: in case **you are the winner**, and in case **you are one of the losers** of your group. You will obtain the highest expected earnings if **your answer equals the actual likelihood of you being the winner**.

Please remember that your earnings in Task 2 are either **€0 or €20**, therefore, your expected earnings are equal to €20 multiplied by the probability of earning the €20 (which is calculated with the formulas in footnote 1).

We provide an example below to illustrate how your earnings depend on your answers (note that the numbers used in this example are not indicative of what constitutes a good or bad answer in this task).

Example: Imagine that among the students taking part in this study, your performance in Task 1 puts you in the **Top 30%**. In other words, 70% of the study participants performed worse than you did and 30% performed better than you did. Recall that, for you to be the group's winner, it must be the case that **all two** of the other members of your group come from the 70% of participants who performed worse than you did. In this example, the probability that this occurs is 49.00% (see the table).

Suppose that your answer is 49.00% in the black slider and Top 30% in the green slider, as shown in the screen below.



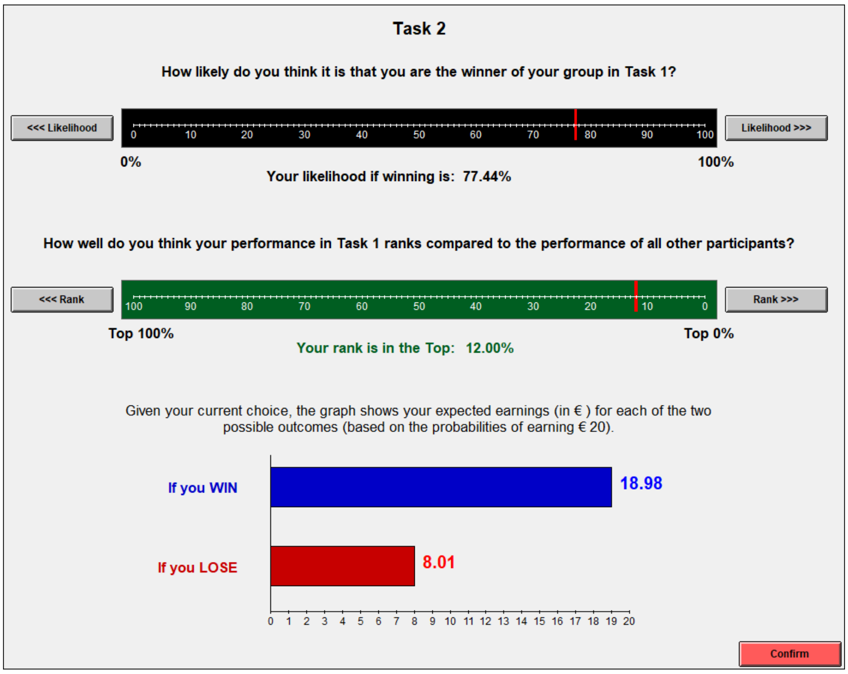
Then, as you can see with the bar graph in the screenshot:

- If you turn out to be the winner of your group, you can expect to earn in Task 2 **€14.80** on average (= €20 × probability of earning €20 if you are the winner).

- If you turn out to be one of the losers of your group, you can expect to earn in Task 2 **€15.20** on average (= €20 × probability of earning €20 if you are one of the losers).

Since the actual likelihood that you are the winner of your group is **49.00%**, this means that **49.00%** of the time you are the group's winner and **51.00%** of the time you are one of the losers. Overall, this means that you can expect to earn in Task 2 **€15.00 on average** (€15.00 = 0.49 × €14.80 + 0.51 × €15.20).

Now let's see what happens if you answer differently. Continue to suppose that your performance places you in the **Top 30%**. However, imagine that this time your answer is 77.44% in the black slider and Top 12% in the green slider, as shown in the screen below.



Then, as you can see with the bar graph in the screenshot:

- If you turn out to be the winner of your group, you can expect to earn in Task 2 **€18.98** on average (€20 × probability of earning €20 if you are the winner).

- If you turn out to be one of the losers of your group, you can expect to earn in Task 2 **€8.01** on average (€20 × probability of earning €20 if you are one of the losers).

Since the actual likelihood that you are the winner of your group is still **49.00%** (remember that you actually are in the Top 30%), this means you can expect to earn in Task 2 **€13.39 on average** (€13.39 = **0.49** × **€18.98** + **0.51** × **€8.01**).

Note that **€13.39** is lower than **€15.00**, which are the expected earnings from reporting 49.00% in the black slider and Top 30% in the green slider.

In conclusion and to reiterate, you will obtain the highest expected earnings in Task 2 if **your answer equals your actual likelihood of being the group's winner in Task 1**.

Once you are done reading, click on the "Next" button on your screen.

Your payment choice in task 1

Next you are going to perform Task 1, but before performing the task, you must choose how you want to be paid for each correct sum in Task 1. Recall that you can choose between **individual pay** and **competitive pay**.

You will be asked to make choices in 5 **different decision sets**. All these decision sets are completely independent of each other. An example of one decision set is displayed in the screenshot below.

	Competitive Pay		Individual Pay
1.	€ 4.00 if you win and € 1.00 if you lose		€ 4.00 with **17%** chance and € 1.00 with **83%** chance
2.	€ 4.00 if you win and € 1.00 if you lose		€ 4.00 with **20%** chance and € 1.00 with **80%** chance
3.	€ 4.00 if you win and € 1.00 if you lose		€ 4.00 with **23%** chance and € 1.00 with **77%** chance
4.	€ 4.00 if you win and € 1.00 if you lose		€ 4.00 with **26%** chance and € 1.00 with **74%** chance
5.	€ 4.00 if you win and € 1.00 if you lose		€ 4.00 with **29%** chance and € 1.00 with **71%** chance
6.	€ 4.00 if you win and € 1.00 if you lose		€ 4.00 with **32%** chance and € 1.00 with **68%** chance
7.	€ 4.00 if you win and € 1.00 if you lose		€ 4.00 with **35%** chance and € 1.00 with **65%** chance
8.	€ 4.00 if you win and € 1.00 if you lose		€ 4.00 with **38%** chance and € 1.00 with **62%** chance
9.	€ 4.00 if you win and € 1.00 if you lose		€ 4.00 with **41%** chance and € 1.00 with **59%** chance
10.	€ 4.00 if you win and € 1.00 if you lose		€ 4.00 with **44%** chance and € 1.00 with **56%** chance

Each decision set consists of a table with a series of choices:

- The left-choices correspond to **competitive pay**. Under competitive pay your earnings in Task 1 depend on your performance and the performance of others in your group. Specifically, if are the winner of your group then you earn the high amount per correct sum, otherwise you earn the low amount per correct sum.

- The right choices correspond to **individual pay**. Under individual pay your earnings in Task 1 depend on your performance and on chance. Specifically, you earn the high amount per correct sum with some probability X [a number between 1 and 100]. To determine your earnings, you will throw two ten-sided dice to randomly generate a number between 1 and 100. If the number you generate is lower than the probability X then you earn the high amount per correct sum, otherwise you earn the low amount per correct sum.

You must decide in every row whether you prefer **individual pay** or **competitive pay**.

Notice that in a decision set, the high and low amounts for competitive pay are the same in all rows. In some decision sets, what varies from row to row is the probability of getting the high amount in individual pay. In other decision sets, what varies from row to row is the high amount in individual pay.

At the end of the experiment, one of the 8 decision sets will be randomly selected. Within the selected decision set, one of the 10 rows will be randomly selected. The type of payment you chose in the selected row will be used to determine how much you will receive per correct sum in Task 1.

Example: Take a look at the choices in the screenshot below. Now, imagine that this decision set is randomly selected for payment and within this decision set, row number 4 is randomly selected. Given that **individual pay** was chosen instead of a **competitive pay** in this row, then:

- With 27% of chance, you will earn €5 per correct sum in Task 1 [the high amount].
- With 73% of chance, you will earn €0 per correct sum in Task 1 [the low amount].

	Competitive Pay	Individual Pay
1.	**€ 6.00 if you win and € 0.00 if you lose**	€ 6.00 with **21%** chance and € 0.00 with **79%** chance
2.	**€ 6.00 if you win and € 0.00 if you lose**	€ 6.00 with **23%** chance and € 0.00 with **77%** chance
3.	€ 6.00 if you win and € 0.00 if you lose	**€ 6.00 with 25% chance and € 0.00 with 75% chance**
4.	€ 6.00 if you win and € 0.00 if you lose	**€ 6.00 with 27% chance and € 0.00 with 73% chance**
5.	€ 6.00 if you win and € 0.00 if you lose	**€ 6.00 with 29% chance and € 0.00 with 71% chance**
6.	€ 6.00 if you win and € 0.00 if you lose	**€ 6.00 with 31% chance and € 0.00 with 69% chance**
7.	€ 6.00 if you win and € 0.00 if you lose	**€ 6.00 with 33% chance and € 0.00 with 67% chance**
8.	€ 6.00 if you win and € 0.00 if you lose	**€ 6.00 with 35% chance and € 0.00 with 65% chance**
9.	€ 6.00 if you win and € 0.00 if you lose	**€ 6.00 with 37% chance and € 0.00 with 63% chance**
10.	€ 6.00 if you win and € 0.00 if you lose	**€ 6.00 with 39% chance and € 0.00 with 61% chance**

Now, imagine that instead of row number 4, the row randomly selected for payment is row number 2. Given that **competitive pay** was chosen instead of **individual pay** in this row, then:

- If you are the group's winner in Task 1, you earn €6 per correct sum [the high amount].
- If you are one of the group's losers in Task 1, you earn €0 per correct sum [the low amount].

Task 3

In Task 3 you will be perform again the same summation task you performed in Task 1. The main difference is that you will be randomly assigned to a **group of <u>six</u> participants** instead of three.

Task 4

Task 4 is like Task 2. In Task 4 you can earn money by answering the following question:

"How likely do you think it is that you are the winner of your group in Task 3?"

Again, your will be able to select your answer by moving the cursors in two different sliders:

- In the black slider, you can select your likelihood of being the winner of your group. Your answer can go from 0% (meaning you are completely certain that you are not the winner of your group) to 100% (meaning you are completely certain that you are the winner of your group).
- In the green slider, you can select how your performance in task 3 ranks compared to the performance of all participants. Your answer can go from Top 100% (you performed worse than ALL other participants of the study) to Top 0% (you performed better than **all** other participants in the study).

Your earnings in Task 4 will be calculated using the same formulas as in Task 2. Recall that you will obtain the highest expected earnings if your answer equals the actual likelihood of you being the winner in Task 3.

One important consideration for Task 4, is that to be the winner in Task 3, you need to be the best in a group of **six**. The table provided in the next page displays the likelihood of being your group's winner in Task 3 depending on each possible rank. Logically, it is harder to be the winner in a group of six than in a group of three. This is why the percentages in the table for Task 4 are lower than the percentages in the table for Task 2.

Group of 6

Your performance is in the Top ...	The likelihood that you are your group's winner is...
0%	100.00%
1%	95.10%
2%	90.39%
3%	85.87%
4%	81.54%
5%	77.38%
6%	73.39%
7%	69.57%
8%	65.91%
9%	62.40%
10%	59.05%
11%	55.84%
12%	52.77%
13%	49.84%
14%	47.04%
15%	44.37%
16%	41.82%
17%	39.39%
18%	37.07%
19%	34.87%
20%	32.77%
21%	30.77%
22%	28.87%
23%	27.07%
24%	25.36%
25%	23.73%
26%	22.19%
27%	20.73%
28%	19.35%
29%	18.04%
30%	16.81%
31%	15.64%
32%	14.54%
33%	13.50%
34%	12.52%
35%	11.60%
36%	10.74%
37%	9.92%
38%	9.16%
39%	8.45%
40%	7.78%
41%	7.15%
42%	6.56%
43%	6.02%
44%	5.51%
45%	5.03%
46%	4.59%
47%	4.18%
48%	3.80%
49%	3.45%
	continues →

Your performance is in the Top ...	The likelihood that you are your group's winner is...
50%	3.13%
51%	2.82%
52%	2.55%
53%	2.29%
54%	2.06%
55%	1.85%
56%	1.65%
57%	1.47%
58%	1.31%
59%	1.16%
60%	1.02%
61%	0.90%
62%	0.79%
63%	0.69%
64%	0.60%
65%	0.53%
66%	0.45%
67%	0.39%
68%	0.34%
69%	0.29%
70%	0.24%
71%	0.21%
72%	0.17%
73%	0.14%
74%	0.12%
75%	0.10%
76%	0.08%
77%	0.06%
78%	0.05%
79%	0.04%
80%	0.03%
81%	0.02%
82%	0.02%
83%	0.01%
84%	0.01%
85%	0.01%
86%	0.01%
87%	0.00%
88%	0.00%
89%	0.00%
90%	0.00%
91%	0.00%
92%	0.00%
93%	0.00%
94%	0.00%
95%	0.00%
96%	0.00%
97%	0.00%
98%	0.00%
99%	0.00%
100%	0.00%

Task 5

This is Task 5 of the experiment. The earnings from this part of the experiment are completely independent from the other tasks. The amount you earn depends **solely on your decisions and on chance**. Moreover, you will not perform further summation tasks.

You will be asked to make choices in **4 different decision tables**. All these decision tables are completely independent of each other. An example of one decision table is displayed in the screenshot below.

	Option A	Option B
1.	€ 28.80 with certainty	€ 72.00 with 50% chance and € 0.00 with 50% chance
2.	€ 30.24 with certainty	€ 72.00 with 50% chance and € 0.00 with 50% chance
3.	€ 31.68 with certainty	€ 72.00 with 50% chance and € 0.00 with 50% chance
4.	€ 33.12 with certainty	€ 72.00 with 50% chance and € 0.00 with 50% chance
5.	€ 34.56 with certainty	€ 72.00 with 50% chance and € 0.00 with 50% chance
6.	€ 36.00 with certainty	€ 72.00 with 50% chance and € 0.00 with 50% chance
7.	€ 37.44 with certainty	€ 72.00 with 50% chance and € 0.00 with 50% chance
8.	€ 38.88 with certainty	€ 72.00 with 50% chance and € 0.00 with 50% chance
9.	€ 40.32 with certainty	€ 72.00 with 50% chance and € 0.00 with 50% chance
10.	€ 41.76 with certainty	€ 72.00 with 50% chance and € 0.00 with 50% chance

Each table has 10 different decisions, each in a different row. Each decision has two options:

- **Option A**, where you can earn a different certain amount in each of the 8 rows.
- **Option B**, where you can earn a high amount with some probability and a low amount with some other probability. Specifically, you earn the high amount with some probability X [a number between 1 and 100]. To determine your earnings, you will throw two ten-sided dice to randomly generate a number between 1 and 100. If the number you generate is lower than the probability X then you earn the high amount, otherwise you earn the low amount.

You can decide for every row whether you prefer **Option A** or **option B**. Option A is the same for every row, while option B takes 8 different amounts, one for each row.

At the end of the experiment, one of the 4 decision tables will be randomly selected. Within the selected table, one of the 10 rows will be randomly selected. The choice you made in that row will determine your earnings of Task 5.