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ABSTRACT

This paper develops a partial-identification methodology for analyzing self-selection into alternative compensation schemes in a laboratory environment. We formulate a model of self-selection in which individuals select the compensation scheme with the largest expected valuation, which depends on individual- and scheme-specific beliefs and non-monetary preferences. We characterize the resulting sharp identified sets for individual-specific willingness-to-pay, subjective beliefs, and preferences, and develop conditions on the experimental design under which these identified sets are informative. We apply our methods to examine gender differences in preference for winner-take-all compensation schemes. We find that what has commonly been attributed to a gender difference in preference for performing in a competition is instead explained by men being more confident than women in their probability of winning a future (though not necessarily a past) competition.

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1 Introduction

The seminal study of Niederle and Vesterlund (2007) finds that men and women differ in their desire to be compensated based on competitive versus noncompetitive compensation schemes in a laboratory setting, and attempts to identify the determinants of this gender gap. Using their experimental design (henceforth referred to as the NV design), Niederle and Vesterlund (2007) find the gender gap in selection into competitive compensation schemes persists conditional on objective performance, beliefs about relative performance, and choice of how to be compensated for a past performance. They attribute this conditional gender gap in selection to a gender gap in preference for performing in competitive environments.

Building on Niederle and Vesterlund (2007)'s study, subsequent papers have applied the NV design to study differences in beliefs and preferences across various groups and settings.[1] However, little attention has been given to the experimental design itself and to the implicit assumptions that their analysis requires using this design.

Our paper begins by re-visiting Niederle and Vesterlund (2007)'s observation that "to the extent that there are gender differences in the participants' beliefs about their future performance and that these influence tournament entry, our study incorrectly attributes such an effect to men and women having different preferences for performing in a competition." Phrased differently, this observation implies that, without certain assumptions, their conclusion that men have a greater non-monetary preference for entering future competitive compensation schemes than women is only one of multiple observationally equivalent explanations for their experimental results. The conclusions asserted under the NV design only follow if all other observationally equivalent explanations are assumed away a priori—for example, by imposing the assumption that individuals' beliefs about their past and future performance are identical.

This paper develops a partial-identification methodology for analyzing self-selection into alternative compensation schemes in laboratory settings given a choice of experimental design and an explicit economic model of selection. In our model, individuals select into the compensation scheme that has the highest expected valuation. Expected valuations are allowed to depend on the potential determinants of self-selection discussed in Niederle and Vesterlund (2007), including subjective beliefs about monetary payoffs and non-monetary preferences for participating in the selected compensation scheme. We allow for rich heterogeneity across individuals: beliefs and preferences are individual-specific and we do not

[1]See Niederle and Vesterlund (2011) for a review, and see Markowsky and Beblo (2022) for a meta analysis. Examples of recent papers that apply the NV design to study differences across other groups include Okudaira, Kinari, Mizutani, Ohtake, and Kawaguchi, 2015 (family structure), Almås, Cappelen, Salvanes, Sørensen, and Tungodden, 2016 (socioeconomic class), and Siddique and Vlassopoulos, 2020 (ethnicity).

impose any restrictions on how they vary across participants or compensation schemes.

We consider the class of experimental designs in which individuals make choices between compensation schemes with different monetary payoffs. We do not rely on proxies for performance beliefs—such as individuals' rank guesses for their relative past performance as in Niederle and Vesterlund (2007)—to subsequently attribute any remaining gender gap to a gender difference in preferences. Instead, we set-identify individuals' belief and preference parameters through their observed choices. We construct identified sets for individual-specific parameters of interest that are sharp given the model and the observed choices. For a large class of experimental designs and set of target parameters, we show that sharp identified sets can be constructed by solving pairs of linear programs. We develop conditions on the experimental design for identified sets on parameters of interest to be bounded and informative.

Our theoretical results imply that the sharp identified sets for our considered belief and preference parameters are uninformative or unbounded under the NV design. Our analysis shows that judicious modifications to the NV design result in informative and bounded identified sets for many of these parameters, and we accordingly design and implement such an experiment.

We analyze the resulting experimental data. Consistent with the previous literature, we find that men on average place a higher value on competitive compensation schemes than women, and that this gender gap increases when considering compensation for a future performance relative to a past performance. However, our results reject the assumptions required under the NV design to conclude that the gender differences in valuations are largely caused by gender differences in preferences. We find that the discrepancy between men and women's willingness to enter a competitive compensation scheme that has commonly been attributed to a gender difference in non-monetary preference for competition is explained instead by men, and especially low ability men, having relatively greater overconfidence in their future (though not necessarily past) probabilities of winning in such competitive environments. We do not find evidence that men and women systematically differ in their taste for competition—and indeed find that women have a positive taste for competing—but do find that they differ substantially in their performance-related beliefs.

The rest of the paper is organized as follows. In Section 2, we briefly discuss the NV design. Section 3 develops our framework for analyzing selection into compensation schemes. Section 4 presents our identification analysis. Sections 5 and 6 introduce our experimental design and present our empirical results. Section 7 concludes.

2 Re-visiting the Niederle-Vesterlund design

Niederle and Vesterlund (2007) provide a thorough discussion of their design, and we now summarize its main aspects. In their design, individuals complete addition tasks in which the goal is to maximize the number of correct answers in the allotted time, and individuals choose whether to be compensated for these performances under a piece-rate (non-competitive) or a tournament (competitive) compensation scheme. Under the piece-rate scheme, payment is 50 cents per correct answer and is determined solely based on an individual's own performance. Under the tournament scheme, the payment is $2 per correct answer, but is only awarded to the individual who performs the best out of a group of four.

Individuals choose between piece-rate and tournament compensation schemes, and their choices are either applied to a past task performance or to a future task performance. In the case of a past task performance, they complete the task, are told their performance (number of correct answers) on that task, and subsequently decide whether they wish to be compensated for the completed task under a piece-rate or tournament compensation scheme. Individuals also provide their rank guess for their relative performance on the task they completed.[2] In the case of a future task performance, they first decide whether they want their next task performance to be compensated under a piece-rate or tournament scheme, and then subsequently perform the task. For both past and future tournament compensation, individuals' performances are compared to the past task performances of the other individuals in their group, which removes the potential for others' compensation choices to affect an individual's decisions. Additionally, in both cases individuals are not given any information about the performances of others. A key difference between the two cases is that in the second case individuals are choosing compensation for a task before they perform it and, therefore, without knowing how they will do.

Under their design, Niederle and Vesterlund (2007) argue that gender differences in preference for performing in a future competitive environment can be identified by the gender difference in the propensity to enter a future tournament, controlling for choice of how to be compensated for a past performance, realized past performance, and past subjective rank guess. The rationale is as follows: whereas "general" factors such as overconfidence and feedback aversion are present in the choices of compensation scheme for both past and future performances, the preference for performing the task in a competitive environment only manifests itself in the decision on future compensation.

However, this identification strategy implicitly allows for only a very limited form of overconfidence.

[2]Rank guess involves providing the number that the individual believes represents the rank of their performance on a completed task out of the group of four individuals.

In particular, the controls used relate to either the individual's own past performance or their self-reported beliefs about the performance of others relative to their own past performance, and do not directly address beliefs about future performance. Niederle and Vesterlund (2007) do not find a statistically significant mean difference between the past and future performances of individuals who choose to enter a future tournament, but beliefs about future performance need not correspond to observed performance.

This issue fundamentally alters the implications of studies using the NV design. Although differing preferences for performing in a competitive environment is one possible explanation for the gender gap observed in these studies, an equally consistent explanation is that men and women differ in beliefs about future performance relative to past performance, and thus future payoffs relative to past payoffs. Although Niederle and Vesterlund (2007) acknowledge the possibility of such threats to their identification strategy, they—and subsequent applications of the design—do not consider the issue further. We formally revisit this issue in Section 4 after first developing our framework.

3 Framework

We analyze laboratory settings that generalize that of Niederle and Vesterlund (2007). There are two key components to our framework: an experimental design which formalizes the process of eliciting choices between compensation schemes at different base-payoffs, and an explicit economic model of selection into compensation schemes. Given these components, we develop a partial-identification methodology to analyze the latent beliefs and preferences that determine selection into compensation schemes.

Our main identification results use the economic model and observed data to construct sharp bounds on target parameters of interest. In doing so, our framework allows the researcher to a priori analyze whether it is possible to form informative bounds on a target parameter. The researcher can accordingly flexibly modify the experimental design while making explicit the assumptions underpinning their analysis.

3.1 Class of experimental designs

We consider the class of experimental designs in which individuals make choices between alternative compensation schemes with different base-payoffs that are applied to task performances. The class of designs generalizes the NV design by allowing for the elicitation of choices between a larger set of compensation schemes and at any number of base-payoffs.

We denote the set of compensation schemes as $\mathcal{J}$, with schemes indexed by j. For any scheme j, we denote (j, p) as a scheme-payoff, where $p > 0$ is the base-payoff. For example, j may denote a past tournament scheme, so that (j, p) denotes the past tournament with, conditional on winning, a compensation of \$$p$ multiplied by the individual's performance.

Niederle and Vesterlund (2007) consider four compensation schemes. Let pt (ft) denote the considered past (future) tournament compensation schemes, and pr (fr) denote the past (future) piece-rate compensation schemes. Then the set of schemes considered in the NV design is $\mathcal{J}_{NV} \equiv \{pt, pr, ft, fr\}$. We generalize this set of schemes by considering two additional compensation schemes, which we denote as fixed pay (f) and future lumpsum tournament (fl). A fixed pay scheme-payoff (f, p) is a fixed cash transfer of \$$p$ that does not depend on performance. A future lumpsum tournament scheme-payoff (fl, p) is the same as a future tournament scheme-payoff except that, conditional on winning, the compensation is performance-invariant. In particular, the winner receives a payoff \$$p$ rather than \$$p$ multiplied by their performance. We collect these considered schemes via the set $\mathcal{J}$.

Definition 1 (Set of Compensation Schemes)**.** Define $\mathcal{J} = \left\{f, \mathcal{J}^p, \mathcal{J}^f\right\}$ where

$$\mathcal{J}^p = \left\{pr, pt\right\} \qquad (\textit{past schemes}),$$
$$\mathcal{J}^f = \left\{ft, fr, fl\right\} \qquad (\textit{future schemes}).$$

Because past and future tournaments and future lumpsum tournaments involve competing against others, we will sometimes refer to these schemes as competitive schemes and the other schemes as non-competitive schemes. Given $\mathcal{J}$, we define a choice experimental design as follows.

Definition 2 (Choice Experimental Design)**.** Let $\mathcal{V} \subseteq \mathcal{J}^2 \times \mathbb{R}^2$ denote the finite set of (j, j', p, q) values, $j \neq j'$, $p, q > 0$, such that the experiment elicits incentive compatible choices between scheme-payoff (j, p) and scheme-payoff (j', q). We call $\mathcal{V}$ the choice experimental design.

Remark 3.1 (Finite Number of Choices)**.** The restriction that $\mathcal{V}$ is a finite set nests the NV design as well as the design we use in our application. Our analysis can be immediately extended to allow for an arbitrary (possibly infinite) number of choices at the cost of additional notational complexity.

For any individual i and any $(j, j', p, q) \in \mathcal{V}$, let $D_{j,j'}(p, q; i)$ denote an indicator variable for i choosing scheme-payoff (j, p) over (j', q). The choice experimental design $\mathcal{V}$ results in the researcher observing choices $D_{i,\mathcal{V}} \equiv \left\{D_{j,j'}(p,q;i)\right\}_{(j,j',p,q)\in\mathcal{V}}$ for each individual i. An experimental design elicits other covariates in addition to $D_{i,\mathcal{V}}$, with our only restriction on these additional covariates being that they include past task performances and, if the researcher is interested in differences across groups like gender, group membership. We accordingly define the observation elicited by the experimental design for each individual i as follows.

Definition 3 (Individual-Level Observation)**.** Consider the set of schemes $\mathcal{J}$ and choice experimental design $\mathcal{V}$. Then the experimental design results in individual-level observation $(D_{i,\mathcal{V}}, X_i)$, where $X_i = [X_{i1}, X_{i2}]$, with

$$X_{i1} \equiv \left(\{S^*_{ij}\}_{j\in\mathcal{J}^p}, G_i\right),$$

$\{S^*_{ij}\}_{j\in\mathcal{J}^p}$ denoting i's realized task performances for past schemes, G_i denoting i's group membership, and with X_{i2} denoting a vector of other covariates.

3.2 Model of selection into compensation schemes

Based on the discussions of Niederle and Vesterlund (2007), we develop a model of selection in which agents facing a choice between alternative compensation schemes choose the scheme with the higher expected valuation. We assume that the individual's valuation (total compensation) from scheme j at base-payoff p is additively separable in monetary and non-monetary components, where the non-monetary component does not depend on the base-payoff. We thus write individual i's valuation for scheme j as a function of base-payoff p as

$$M_{ij}(p) + R_{ij}. \tag{1}$$

For all schemes we consider, monetary payoff function $M_{ij}(p)$ takes the form

$$M_{ij}(p) = W_{ij} \cdot m_j(S_{ij}) \cdot p, \tag{2}$$

where $W_{ij} \in \{0,1\}$ denotes whether i would receive monetary compensation if selecting into scheme j, S_{ij} is the performance for i under scheme j, and $m_j(S_{ij})$ is defined by

$$m_j(S_{ij}) \equiv \begin{cases} 1 & \text{if } j \in \{f, fl\} \\ S_{ij} & \text{if } j \notin \{f, fl\} \end{cases}. \tag{3}$$

For competitive schemes, W_{ij} depends on S_{ij} as well as the performance of other individuals in i's group. For example, if j is a past or future tournament, $W_{ij} = 1$ indicates that individual i would win (have the highest performance in their group) if selecting into scheme j, and since compensation is base-payoff multiplied by performance, $m_j(S_{ij}) = S_{ij}$.

Turning to the non-monetary component, NV hypothesize that it may depend on two factors: the value of receiving feedback about whether the individual won or not, which they call feedback aversion, and the cost of performing the task. In discussing the interpretation of feedback aversion, NV note that some individuals may prefer not learning that they lost in a competition and others may derive value from learning that they won. We thus assume that non-monetary compensation R_{ij} takes the form

$$R_{ij} = W_{ij} \cdot \tilde{\eta}_{ij}(1) + (1 - W_{ij}) \cdot \tilde{\eta}_{ij}(0) + \tilde{c}_{ij}, \tag{4}$$

where $\tilde{\eta}_{ij}(1)$ and $\tilde{\eta}_{ij}(0)$ denote the cost of feedback aversion of respectively winning or losing if the individual were to select into scheme j, and $\tilde{c}_{ij}$ is the cost of performing the task if selecting into the task, where we allow these costs to be random from the individual's perspective and we do not constrain their sign. Recall that the valuation is from the individual's perspective at the time she is selecting into compensation schemes. Thus, $\tilde{c}_{ij} = 0$ for any past scheme j as the cost of performing a past task has already been incurred prior to the selection decision.

Let $\mathbb{E}_i$ denote the expectation operator integrating against individual i's subjective beliefs at the time she is selecting into compensation schemes, at which point S_{ij} for j past tournament and past piece rate have already been realized and observed by the individual and are in her information set. Individual i's expected valuation of scheme j as a function of base-payoff can be written as

$$\begin{aligned} V_{ij}(p) \equiv\ & \mathbb{E}_i \left[M_{ij}(p) + R_{ij} \right] \\ =\ & \{\pi_{ij} \cdot \mu_{ij}\}\ p + \{\pi_{ij} \cdot \eta_{ij}(1) + (1 - \pi_{ij}) \cdot \eta_{ij}(0) + c_{ij}\}, \end{aligned} \tag{5}$$

where

$$\begin{aligned} \pi_{ij} =\ & \mathbb{P}_i[W_{ij} = 1], \\ \mu_{ij} =\ & \mathbb{E}_i \left[m_j(S_{ij}) \mid W_{ij} = 1 \right], \\ \eta_{ij}(w) =\ & \mathbb{E}_i \left[\tilde{\eta}_{ij}(w) \mid W_{ij} = w \right], \quad w = 0, 1, \\ c_{ij} =\ & \mathbb{E}_i \left[\tilde{c}_{ij} \right]. \end{aligned} \tag{6}$$

Let $\theta_{ij} = (\theta_{ij}^{[1]}, \theta_{ij}^{[2]})$, where $\theta_{ij}^{[1]} = (\pi_{ij}, \mu_{ij})$ denotes i's performance-related belief parameters and $\theta_{ij}^{[2]} = (\eta_{ij}(0), \eta_{ij}(1), c_{ij})$ denotes her (expected) preference parameters. Since V_{ij} only depends on i through θ_{ij}, we will define $V_j(p; \theta_{ij}) \equiv V_{ij}(p)$.

We will impose restrictions on the individual's performance-related beliefs and preference parameters that are implied by the particular compensation scheme j. Since the concepts of winning and, by extension, of feedback aversion are only defined for competitive schemes, we impose that $\pi_{ij} = 1$ and $\eta_{ij}(1) = \eta_{ij}(0) = 0$ for all non-competitive schemes. For competitive schemes, $\pi_{ij} = \mathbb{P}_i[W_{ij} = 1] \in [0, 1]$ and this value depends on the individual's beliefs about their probability of winning. Since individuals observe their realized past task performance when considering the valuation of a past scheme, we impose that, for all $j \in \mathcal{J}^p$, S_{ij} is degenerate and equal to the realized past performance S^*_{ij} so that $\mu_{ij} = S^*_{ij}$. Because realized past task performances are always positive in practice, we impose that $S^*_{ij} > 0$ for all $j \in \mathcal{J}^p$.[3] Since individuals performed the task (and incurred any cost of performing the task) prior to considering the valuation of a past scheme, we accordingly impose that $\tilde{c}_{ij} = 0$ so that $c_{ij} = 0$ for all $j \in \mathcal{J}^p$. Collecting these restrictions, we have that $\theta_{ij} \in \Theta_j$ where

$$\Theta_j \equiv \begin{cases} \{1\} \times \{1\} \times \{0\} \times \{0\} \times \{0\} & \text{if } j = f \\ \{1\} \times \mathbb{N}^+ \times \{0\} \times \{0\} \times \{0\} & \text{if } j = pr \\ [0,1] \times \mathbb{N}^+ \times (-\infty, \infty) \times (-\infty, \infty) \times \{0\} & \text{if } j = pt \\ \{1\} \times [0, \infty) \times \{0\} \times \{0\} \times (-\infty, \infty) & \text{if } j = fr \\ [0,1] \times [0, \infty) \times (-\infty, \infty) \times (-\infty, \infty) \times (-\infty, \infty) & \text{if } j = ft \\ [0,1] \times \{1\} \times (-\infty, \infty) \times (-\infty, \infty) \times (-\infty, \infty) & \text{if } j = fl. \end{cases} \tag{7}$$

We will write $\theta_i \equiv \{\theta_{ij}\}_{j \in \mathcal{J}}$, $\theta_i \in \Theta \subseteq \mathbb{R}^K$, where $K \equiv 5|\mathcal{J}|$ and $\Theta \equiv \prod_{j \in \mathcal{J}} \Theta_j$. Together, the model and these restrictions on θ_i lead us to define our model of selection, which we refer to as ASVM (Additively-Separable Valuation Model).

Assumption 1 (ASVM)**.** Given choice experimental design $\mathcal{V}$, individual i satisfies Assumption 1 if they have associated individual-level observation $(D_{i,\mathcal{V}}, X_i)$ and parameters $\theta_i \in \Theta$ such that

1. $\mu_{ij} = S^*_{ij}$ for all $j \in \mathcal{J}^p$, and

[3]This requirement is not necessary: the upcoming identification analysis can be trivially modified to separately consider the case where $S^*_{ij} = 0$. However, doing so would introduce additional notation. In practice, individuals have ample time to correctly complete at least one addition task in the NV design, and this also holds in our application.

2. for all $(j, j', p, q) \in \mathcal{V}$,

$$D_{j,j'}(p, q; i) = \mathbb{1}\Big[V_j(p; \theta_{ij}) \geq V_{j'}(q; \theta_{ij'})\Big]. \tag{8}$$

Under Assumption 1: (1) the individual's subjective expected performance equals their realized performance for a past task for which they have already been told their realized performance; and (2) for all choices, they choose the option with the higher expected valuation, i.e., the higher $V_j(p; \theta_{ij})$ term.

From equation (5), we have that

$$V_j(p; \theta_{ij}) = \delta(\theta_{ij}^{[1]})\ p + \gamma(\theta_{ij}), \tag{9}$$

with

$$\delta(\theta_{ij}^{[1]}) = \pi_{ij} \cdot \mu_{ij}, \tag{10}$$

$$\gamma(\theta_{ij}) = \psi(\theta_{ij}) + c_{ij}, \tag{11}$$

where $\psi(\theta_{ij})$ is the expected value of feedback aversion,

$$\psi(\theta_{ij}) = \pi_{ij} \cdot \eta_{ij}(1) + (1 - \pi_{ij}) \cdot \eta_{ij}(0). \tag{12}$$

We thus have that valuation $V_j(p; \theta_{ij})$ is an affine function of base-payoffs with slope parameter that only depends on performance beliefs $\theta_{ij}^{[1]}$ and intercept that depends on both beliefs $\theta_{ij}^{[1]}$ and preference parameters $\theta_{ij}^{[2]}$. This linear form with a non-negative slope coefficient on base-payoff will play a critical role in our analysis.

For scheme $j \in \mathcal{J}$, define

$$\beta(\theta_{ij}) \equiv (\delta(\theta_{ij}^{[1]}), \gamma(\theta_{ij})), \tag{13}$$

$$\lambda(\theta_{ij}) \equiv (\pi_{ij}, \mu_{ij}, \psi(\theta_{ij}), c_{ij}). \tag{14}$$

Thus, $\beta(\theta_{ij})$ collects the slope and intercept parameters that determine valuations, which respectively correspond to the expected monetary (at base-payoff $p = 1$) and non-monetary values for scheme j. Note that $\beta(\theta_{ij})$ only depends on θ_i through $\lambda(\theta_{ij})$, which collects the key parameters that underlie our economic model for scheme j.

Remark 3.2 (Choices as Functions of $\beta(\theta_{ij})$)**.** For any $(j, j', p, q) \in \mathcal{V}$, the selection model of equation (8) can be rewritten as

$$D_{j,j'}(p, q; i) = \mathbb{1}\left[\delta(\theta_{ij}^{[1]})\ p + \gamma(\theta_{ij}) \geq \delta(\theta_{ij'}^{[1]})\ q + \gamma(\theta_{ij'})\right]. \tag{15}$$

Remark 3.3 (Risk Neutrality)**.** Our analysis is based on the assumption that individuals exhibit risk-neutral behavior for the choice of compensation scheme in the laboratory experiment given the low stakes involved. Although Niederle and Vesterlund (2007) briefly mention risk preferences as a possible factor that may explain why genders differ in their propensity to enter tournaments, their analysis does not explicitly consider risk preferences. In our experiment, we elicit risk preferences following the design of Holt and Laury (2002). We find that although participants are slightly risk averse on average, their elicited risk preferences do not predict tournament valuations.[4] Consistent with other studies using the design of Holt and Laury (2002), we do not find a significant gender difference in elicited risk attitudes.[5] Furthermore, as discussed in Remark 4.3, there are testable restrictions from the assumption of risk neutrality, and we find that the vast majority of elicited choices are consistent with risk-neutral behavior. Finally, assuming individuals are risk-neutral simplifies our analysis and leads to tractable and computationally feasible characterizations of identified sets for belief and preference parameters. We note that our utility function is observationally equivalent to rank-dependent utility with a linear utility function. That is, beliefs in our model can be interpreted as decision weights in a rank-dependent utility model. We accordingly leave the corresponding analysis without risk neutrality for future work.

3.3 Target parameters

We construct individual-level identified sets for functions of the belief and preference parameters, which we then aggregate to bound population-level quantities.

Definition 4 (Target Parameter)**.** A target parameter for individual i is a real-valued target function $\tau : \mathbb{R}^K \to \mathbb{R}$ evaluated at θ_i. We denote the target parameter as $\tau_i^\star \equiv \tau(\theta_i)$.

Examples of target parameters we will consider include, for $j \in \mathcal{J}$, the valuation $V_j(p; \theta_{ij})$, components of $\beta(\theta_{ij})$, and components of $\lambda(\theta_{ij})$. The target parameters $V_j(p; \theta_{ij})$ determine selection. Recall from equation (9) that $V_j(p; \theta_{ij})$ is an affine function of p parameterized by $\beta(\theta_{ij})$. The first component of

[4] We discuss these results in greater detail in Subsection 6.1 and Online Appendix E.

[5] Filippin and Crosetto (2016) survey studies using the design of Holt and Laury (2002) and find that out of 54 studies, less than 10% show significant gender differences in risk attitudes.

$\beta(\theta_{ij})$, the slope term $\delta(\theta_{ij}^{[1]})$, can be interpreted as i's subjective expected monetary compensation if base-payoff were \$1 and is a function of i's performance-related beliefs. The second component of $\beta(\theta_{ij})$, the intercept term $\gamma(\theta_{ij})$, is i's expected non-monetary compensation, and is a function of i's subjective probability of winning and preference parameters. Analyzing components of $\beta(\theta_{ij})$ thus gives insight into the relative role of performance-related beliefs versus preferences in driving differences in valuations and thus differences in selection into compensation schemes. Finally, examining individual components of $\lambda(\theta_{ij})$ allows us to examine the key parameters that underlie our economic model.

3.4 Identified sets

We call a set an identified set for individual i's given target parameter if it is a known function of individual i's observation, $(D_{i,\mathcal{V}}, X_i)$, that contains individual i's true parameter value. We will use two criteria when evaluating identified sets: whether it is informative, and whether it is sharp. We call an identified set informative if it is strictly tighter than the set implied by the parameter space Θ, and we call an identified set sharp if it is the smallest possible identified set given the assumptions and the individual's observation. Given our model and assumptions, a given parameter is consistent with the individual's observation if it is consistent with the individual's past realized performances and the individual's choices. We will additionally consider whether the identified set is sharp relative to only using choice observations between specified pairs of schemes. In particular, defining

$$\mathcal{S} \equiv \big\{(j, j') \mid \exists\ (p, q) \text{ s.t. } (j, j', p, q) \in \mathcal{V}\big\}, \tag{16}$$

so that $\mathcal{S}$ is the set of (j, j') scheme pairs for which the experiment elicits choices between j and j', we will also consider whether an identified set is sharp relative to using choice observations between pairs of schemes in $\mathcal{S}' \subseteq \mathcal{S}$. In the following, for any function f and set A, a subset of the domain of f, we will write $f(A)$ for the image of A under f.

Definition 5 (Identified Sets)**.** Suppose individual i satisfies Assumption 1. Define

$$\tilde{\Theta}_i \equiv \left\{\theta \in \Theta \;\middle|\; \mu_j = S^*_{ij} \;\; \forall\ j \in \mathcal{J}^p\right\}, \tag{17}$$

and for $\mathcal{S}' \subseteq \mathcal{S}$ define

$$\Theta_i^\star(\mathcal{S}') \equiv \left\{\theta \in \tilde{\Theta}_i \;\middle|\; D_{j,j'}(p,q;i) = \mathbb{1}\left[V_j(p;\theta_j) \geq V_{j'}(q;\theta_{j'})\right] \;\; \forall\, (j,j',p,q) \in \mathcal{V} \text{ s.t. } (j,j') \in \mathcal{S}'\right\}. \tag{18}$$

Let $\Theta_i^\star \equiv \Theta_i^\star(\mathcal{S})$. Let $\Upsilon_i = g(D_{i,\mathcal{V}}, X_i)$ for some known set-valued function g. Then, for any function $f : \mathbb{R}^K \mapsto \mathbb{R}^L$, Υ_i is an identified set for $f(\theta_i)$ if $f(\theta_i) \in \Upsilon_i$, is informative for $f(\theta_i)$ if $f(\theta_i) \in \Upsilon_i$ and $\Upsilon_i \subsetneq f(\tilde{\Theta}_i)$, is the $\mathcal{S}'$-sharp identified set for $f(\theta_i)$ if $\Upsilon_i = f\left(\Theta_i^\star(\mathcal{S}')\right)$, and is the sharp identified set for $f(\theta_i)$ if $\Upsilon_i = f\left(\Theta_i^\star\right)$.

Here, $\tilde{\Theta}_i$ corresponds to the parameter space implied by the model restrictions. Because $\tilde{\Theta}_i$ is the product space of $j-$specific spaces, we can write it as $\tilde{\Theta}_i = \prod_{j\in\mathcal{J}} \tilde{\Theta}_{ij}$. $\Theta_i^\star(\mathcal{S}')$ is the subspace that exhausts choices in $\mathcal{S}'$, and $\Theta_i^\star$ is the subspace that exhausts all observed choices. Following Remark 3.2, we can also rewrite the constraints in (18) as functions of $\{\beta(\theta_{ij})\}_{j\in\mathcal{J}}$. Note that, taking f to be the identity function, the definition implies that $\Theta_i^\star(S')$ is the $\mathcal{S}'$-sharp identified set for θ_i and $\Theta_i^\star$ is the sharp identified set for θ_i.

Remark 3.4 (Parameters that are Trivially Point-Identified)**.** Our parameter space restriction (7) implies that $\tilde{\Theta}_{i,f}$ is a point, while our parameter space restriction and Assumption 1 imply that $\tilde{\Theta}_{i,pr}$ is a point:

$$\tilde{\Theta}_{i,pr} = \{1\} \times S_{i,pr}^* \times \{0\} \times \{0\} \times \{0\}.$$

While $\theta_{i,f}$ and $\theta_{i,pr}$, and thus any functions of them, are immediately point-identified, the same is not true for the parameters that determine the expected valuation of the remaining schemes. In the following, we thus analyze identification of those target parameters that are functions of θ_{ij} for $j \in \mathcal{J} \setminus \{f, pr\}$.

3.5 Payoff indifference sets

Payoff indifference sets will play a critical role in our identification analysis, and are defined as follows:

Definition 6 (Payoff Indifference Set)**.** Define

$$P_{j,j'} \equiv \{p \mid \exists\, q \text{ s.t. } (j,j',p,q) \in \mathcal{V}\}, \tag{19}$$

so that $P_{j,j'}$ is the set of base payoffs p for scheme j for which the experiment elicits choices between scheme-payoff (j,p) and scheme-payoff (j',q) for some q. Define

$$Q_{j,j',p} \equiv \{q \mid (j,j',p,q) \in \mathcal{V}\}, \tag{20}$$

so that $Q_{j,j',p}$ is the set of q values for which individuals choose between (j,p) and (j',q). For any $(j,j') \in \mathcal{S}$, $p \in P_{j,j'}$, define $q_{l,(j,j')}(p;i) = -\infty$ if $D_{j,j'}(p,q;i) = 0$ for all $q \in Q_{j,j',p}$, and

$$q_{l,(j,j')}(p;i) \equiv \max\left\{q \;\middle|\; (j,j',p,q) \in \mathcal{V} \text{ and } D_{j,j'}(p,q;i) = 1\right\} \tag{21}$$

otherwise. Define $q_{u,(j,j')}(p;i) = \infty$ if $D_{j,j'}(p,q;i) = 1$ for all $q \in Q_{j,j',p}$, and

$$q_{u,(j,j')}(p;i) \equiv \min\left\{q \;\middle|\; (j,j',p,q) \in \mathcal{V} \text{ and } D_{j,j'}(p,q;i) = 0\right\} \tag{22}$$

otherwise. We call $[q_{l,(j,j')}(p;i), q_{u,(j,j')}(p;i)]$ the individual's payoff indifference set (for scheme-payoff (j,p) relative to j').

Thus, $q_{l,(j,j')}(p;i)$ is defined as the largest base-payoff q for which individual i chooses scheme-payoff (j,p) over (j',q), while $q_{u,(j,j')}(p;i)$ is defined as the smallest base-payoff q for which individual i chooses scheme-payoff (j',q) over (j,p). From our selection model (equation 8) and that $V_{j'}(q;\theta_{ij'})$ is (weakly) increasing in q, it follows that $q_{l,(j,j')}(p;i) \leq q_{u,(j,j')}(p;i)$, which makes the payoff indifference set well-defined as an interval.

Definition 7 (Payoff Indifference Points)**.** Suppose there exists a unique $q_i^\star \in \mathbb{R}$ such that $V_j(p;\theta_{ij}) = V_{j'}(q_i^\star;\theta_{ij'})$. Then we call $q_i^\star$ the payoff indifference point for (j,j',p), which, when it exists, will necessarily satisfy

$$q_i^\star \in \left[q_{l,(j,j')}(p;i) \;,\; q_{u,(j,j')}(p;i)\right]. \tag{23}$$

In the special case where $j' = f$, the payoff indifference point will necessarily exist with $q_i^\star = V_j(p;\theta_{ij})$, so that

$$V_j(p;\theta_{ij}) \in \left[q_{l,(j,f)}(p;i) \;,\; q_{u,(j,f)}(p;i)\right]. \tag{24}$$

In other words, the target parameter $V_j(p;\theta_{ij})$ is set-identified by the payoff indifference set for (j,p) relative to f.

Remark 3.5 (Bounded Payoff Indifference Sets)**.** By their definitions, $q_{l,(j,f)}(p;i)$ and $q_{u,(j,f)}(p;i)$ will be finite if $D_{j,f}(p,q_0;i) = 0$ and $D_{j,f}(p,q_1;i) = 1$ for some $q_0, q_1 \in Q_{j,f,p}$, equivalently, if $q_1 < V_j(p;\theta_{ij}) < q_0$.

Thus, the identified set on $V_j(p;\theta_{ij})$ from equation (24) will be bounded w.p.1 if

$$P[\min Q_{j,f,p} < V_j(p;\theta_{ij}) < \max Q_{j,f,p}] = 1. \tag{25}$$

Additionally, equation (25) implies that $P[q_{l,(j,f)}(p;i) \in Q_{j,f,p}] = P[q_{u,(j,f)}(p;i) \in Q_{j,f,p}] = 1$.

4 Identification analysis

We use payoff indifference sets to characterize identified sets for arbitrary target parameters in Subsection 4.1, and we specialize the results to characterize the identified sets for the underlying parameters of our economic model in Subsection 4.2. We state necessary and sufficient conditions for these identified sets to be informative. In Subsection 4.3 we consider the implications of our analysis for experimental design.

Our identification analysis focuses on identified sets that only use choices where the alternative is fixed pay. Our rationale for doing so is based on robustness to misreported choices. We speculate that it is cognitively less challenging for subjects to choose between a compensation scheme and fixed pay than between one compensation scheme and another non-fixed pay compensation scheme, and thus easier for individuals to correctly report choices versus fixed pay than versus other schemes. This speculation is supported by Chew, Miao, Shen, and Zhong (2022), who show that choices between two alternative lotteries result in more inconsistent responses than choices between a lottery and a fixed, certain payment. In addition, using only elicited choices against fixed pay is more robust than using the full set of elicited choices as the latter allows a misreport in one choice to potentially invalidate the implied identified sets for the parameters of all schemes. We will use the elicited choices between pairs of non-fixed pay alternatives in Section 5 when analyzing differences in average payoff indifference sets across groups, but not for identifying the underlying parameters of our economic model.

4.1 Characterizing identified sets

Define $\mathcal{S}_f \subseteq \mathcal{S}$ as the restriction of scheme choices to choices where the alternative is fixed pay, so that

$$\mathcal{S}_f \equiv \{(j,j') \in \mathcal{S} \mid j' = f\}.$$

We are interested in constructing identified sets that are sharp relative to $\mathcal{S}_f$. We begin with two observations. First, since $V_{j'}(q;\theta_{j'})$ is (weakly) increasing in q for any candidate θ, if the model with parameter θ is consistent with observed $D_{j,j'}(p,q;i) = 1$ for some q, then it is consistent with observed $D_{j,j'}(p,q';i) = 1$ for all $q' < q$. Likewise, if the model with parameter θ is consistent with observed $D_{j,j'}(p,q;i) = 0$ for some q, then it is consistent with observed $D_{j,j'}(p,q';i) = 0$ for all $q' > q$. This suggests that we can determine whether the model with a particular candidate parameter value is consistent with all observed choices simply by checking whether it is consistent with the payoff indifference sets. When the alternative is fixed pay, this observation trivially holds as $V_f(q;\theta_f) = q$, and the indifference sets take the simple form as in (24).

Second, when assessing whether a vector θ belongs to the $\mathcal{S}_f$-sharp identified set for θ_i, observe that constraints on the subvector θ_j arising from the $j-$specific parameter space and choices between scheme j and fixed pay do not impose any restrictions on the subvector θ_{-j}. As such, we can assess whether θ belongs to the identified set by separately considering whether each subvector θ_j satisfies the requisite $j-$specific constraints. The following theorem formalizes these observations and characterizes the $\mathcal{S}_f$-sharp identified set for θ_i.

Theorem 1. *Suppose individual i satisfies Assumption 1. Then the $\mathcal{S}_f$-sharp identified set for θ_i is characterized by*

$$\Theta_i^\star(\mathcal{S}_f) = \prod_{j:(j,f)\in\mathcal{S}_f} \left\{\theta_j \in \tilde{\Theta}_{ij} \;\middle|\; \delta(\theta_j^{[1]})\ p + \gamma(\theta_j) \in \left[q_{l,(j,f)}(p;i),\ q_{u,(j,f)}(p;i)\right]\ \forall\ p \in P_{j,f}\right\}, \tag{26}$$

and thus $\tau(\Theta_i^\star(\mathcal{S}_f))$ is the $\mathcal{S}_f$-sharp identified set for any target parameter $\tau_i^\star$.

The proof of Theorem 1 is in Online Appendix B and follows from the above arguments. The theorem states that the identified set for θ_i that exploits all of individual i's choices against fixed pay is the set of θ such that, for each scheme j such that the individual chooses between scheme j and fixed pay, the resulting line $\delta(\theta_j^{[1]})\ p + \gamma(\theta_j)$ intersects the individual's payoff indifference sets for scheme j relative to fixed pay. The bounds on θ_i will necessarily be sharp if $\mathcal{S}_f = \mathcal{S}$, i.e., if all choices are against fixed pay.

4.2 Analysis of key parameters underlying the economic model

We now specialize our identification analysis to considering slope and intercept parameters (components of $\beta(\theta_{ij})$), and preference parameters (components of $\lambda(\theta_{ij})$) for $j \in \mathcal{J} \setminus \{f, pr\}$, which following Remark

3.4 are those schemes for which θ_{ij} is not immediately point identified. For any $j \in \mathcal{J} \setminus \{f, pr\}$, define

$$\mathcal{B}_{i,(j,f)} \equiv \left\{ (\delta, \gamma) \in A_{ij} \times \mathbb{R} \;\middle|\; \delta\ p + \gamma \in \left[q_{l,(j,f)}(p; i),\ q_{u,(j,f)}(p; i)\right] \ \forall\ p \in P_{j,f} \right\}, \tag{27}$$

where

$$A_{ij} = \begin{cases} [0, S^*_{ij}] & \text{for } j = pt, \\ [0, \infty) & \text{for } j \in \{fr, ft\}, \\ [0, 1] & \text{for } j = fl. \end{cases} \tag{28}$$

Let $\mathcal{B}^{[k]}_{i,(j,f)}$ denote the projection of $\mathcal{B}_{i,(j,f)}$ onto its kth component. Also define $\delta_{ij} \equiv \delta(\theta^{[1]}_{ij})$ and $\gamma_{ij} \equiv \gamma(\theta_{ij})$ so that $\beta(\theta_{ij}) = (\delta_{ij}, \gamma_{ij})$. The following theorem characterizes the identified sets for the components of $\beta(\theta_{ij})$.

Theorem 2. *Suppose individual i satisfies Assumption 1. Then, for $j \in \mathcal{J} \setminus \{f, pr\}$,*

1. $(\delta_{ij}, \gamma_{ij}) \in \mathcal{B}_{i,(j,f)}$.
2. $\mathcal{B}^{[1]}_{i,(j,f)}$ *and* $\mathcal{B}^{[2]}_{i,(j,f)}$ *are $\mathcal{S}_f$-sharp for δ_{ij} and γ_{ij} respectively, and these sets are intervals:*

$$\mathcal{B}^{[1]}_{i,(j,f)} = [\delta_{ij,l},\ \delta_{ij,u}],$$
$$\mathcal{B}^{[2]}_{i,(j,f)} = [\gamma_{ij,l},\ \gamma_{ij,u}].$$

Result 1. of Theorem 2 follows from Theorem 1 and the specification of Θ in (7). Result 2. is proven in Online Appendix B. Our proof that $\mathcal{B}^{[1]}_{i,(j,f)}$ is $\mathcal{S}_f$-sharp is based on the parameter space for θ being the product space of $j-$specific parameter spaces, that $\beta(\tilde{\Theta}_{ij}) = A_{ij} \times \mathbb{R}$, and appealing to Theorem 1. That this set is an interval follows since, for any $(\delta_1, \gamma_1), (\delta_2, \gamma_2)$ and for any δ^* between δ_1 and δ_2, there exists a γ^* between γ_1 and γ_2 such that the line $\delta^*\ p + \gamma^*$ lies in-between the lines $\delta_1\ p + \gamma_1$ and $\delta_2\ p + \gamma_2$ for all p. The case for $\mathcal{B}^{[2]}_{i,(j,f)}$ follows analogously.

Remark 4.1 (Point-Identified Valuations)**.** Suppose $q_{l,(j,f)}(p; i) = q_{u,(j,f)}(p; i)\ \forall\ p \in P_{j,f}$, which, from equation (24), is equivalent to $V_j(p; \theta_{ij})$ being point identified for $p \in P_{j,f}$. Since two points define a line, we have that $(\delta_{ij}, \gamma_{ij})$ is point identified if $|P_{j,f}| \geq 2$ and over-identified if $|P_{j,f}| \geq 3$.

Remark 4.2 (Necessary and Sufficient Conditions)**.** A necessary condition for $[\delta_{ij,l},\ \delta_{ij,u}]$ to be informative is that $|P_{j,f}| \geq 2$. A sufficient condition for this interval and for $[\gamma_{ij,l},\ \gamma_{ij,u}]$ to both be bounded and informative is that there exists $p_1, p_2 \in P_{j,f}$ with $p_2 > p_1$ such that

$$\frac{\Big(q_{u,(j,f)}(p_2;i) - q_{l,(j,f)}(p_2;i)\Big) + \Big(q_{u,(j,f)}(p_1;i) - q_{l,(j,f)}(p_1;i)\Big)}{p_2 - p_1} < \sup A_{ij}. \tag{29}$$

See Online Appendix B for the proof.

Using that $\sup A_{ij} \geq 1$, a sufficient condition for equation (29) to hold is that

$$\Big(q_{u,(j,f)}(p_2;i) - q_{l,(j,f)}(p_2;i)\Big) + \Big(q_{u,(j,f)}(p_1;i) - q_{l,(j,f)}(p_1;i)\Big) < p_2 - p_1. \tag{30}$$

Suppose that equation (25) holds for $p = p_1, p_2$. Then each term on the left hand side of (30) is an element of Q_{j,f,p_1} or Q_{j,f,p_2}, where $Q_{j,f,p}$ was defined in equation (20), and thus a sufficient condition for (30) and thus for (29) to hold is that

$$\max_{k=1,2} \max_{q \in Q_{j,f,p_k}} \min_{q' \in Q_{j,f,p_k} \setminus \{q\}} |q - q'| < \frac{p_2 - p_1}{2}. \tag{31}$$

Remark 4.3 (Testing Risk Neutrality)**.** Our analysis relies on our assumption of risk neutrality to obtain valuations that are linear in base-payoffs. Theorem 2 immediately implies a testable restriction from risk neutrality for any j such that $|P_{j,f}| \geq 3$: in particular, it implies that there exists values of (δ, γ) such that the line $\delta\, p + \gamma$ intersects the intervals $\big\{\big[q_{l,(j,f)}(p;i),\ q_{u,(j,f)}(p;i)\big] \;\big|\; p \in P_{j,f}\big\}$.

We now consider the individual components of $\lambda(\theta_{ij})$. Define $\psi_{ij} \equiv \psi(\theta_{ij})$. Recalling that $\lambda(\theta_{ij}) = (\pi_{ij}, \mu_{ij}, \psi_{ij}, c_{ij})$, the following theorem characterizes the identified sets for the individual components of this vector.

Theorem 3. *Suppose individual i satisfies Assumption 1. Then for any $j \in \mathcal{J} \setminus \{f, pr\}$ and target parameter $\tau_i^\star = \lambda(\theta_{ij})^{[k]}$ corresponding to the kth component of $\lambda(\theta_{ij})$,*

1. *The $\mathcal{S}_f$-sharp identified set for $\tau_i^\star$ is given in Table 1.*
2. *The sharp identified set for $\tau_i^\star$ is uninformative for $\tau_i^\star \in \{\psi_{i,ft}, \psi_{i,fl}, c_{i,ft}, c_{i,fl}\}$, is unbounded for $\tau_i^\star = \mu_{i,ft}$, and is uninformative up to taking the closure for $\tau_i^\star = \pi_{i,ft}$.*

The theorem is proven in Online Appendix B, with a proof based on Theorem 1 and the definitions of $\tilde{\Theta}_{ij}$ and $\beta(\theta_{ij})$.

Table 1: $\mathcal{S}_f$-sharp identified sets for individual preference parameters.

Scheme j	$\pi_{ij} \in$	$\mu_{ij} \in$	$\psi_{ij} \in$	$c_{ij} \in$
Past Tournament	$[\delta_{ij,l}/S^*_{ij}, \delta_{ij,u}/S^*_{ij}]$	$\{S^*_{ij}\}$	$[\gamma_{ij,l}, \gamma_{ij,u}]$	$\{0\}$
Future Piece Rate	$\{1\}$	$[\delta_{ij,l}, \delta_{ij,u}]$	$\{0\}$	$[\gamma_{ij,l}, \gamma_{ij,u}]$
Future Tournament	$\begin{cases} [0,1] & \text{if } 0 \in \delta(\Theta_i^\star(\mathcal{S}_f)) \\ (0,1] & \text{o/w} \end{cases}$	$[\delta_{ij,l}, \infty)$	$(-\infty, \infty)$	$(-\infty, \infty)$
Future Lumpsum Tournament	$[\delta_{ij,l}, \delta_{ij,u}]$	$\{1\}$	$(-\infty, \infty)$	$(-\infty, \infty)$

Remark 4.4 (Set Identification by Solving Linear Programs)**.** Results 1. and 2. of Theorem 2 imply that we can construct the $\mathcal{S}_f$-sharp identified sets $[\delta_{ij,l},\ \delta_{ij,u}]$ and $[\gamma_{ij,l},\ \gamma_{ij,u}]$ by solving pairs of linear programs that respectively minimize (maximize) δ or γ subject to (δ, γ) lying in (27). Result 1. of Theorem 3 implies that we can then plug the endpoints of these intervals into the expressions in Table 1 to calculate $\mathcal{S}_f$-sharp identified sets on $\tau_i^\star \in \{\pi_{ij}, \mu_{ij}, \psi_{ij}, c_{ij}\}$.

Remark 4.5. While our primary reason to exclusively use $\mathcal{S}_f$ for identification of target parameters is for robustness to misreporting, there is an additional computational advantage of doing so. We've shown that we can construct identified sets for our target parameters by solving pairs of straightforward linear programs. In contrast, more generally, the sharp identified sets for our target parameters need not be an interval, and the programs based on the analogue of Theorem 1 presented in Online Appendix C to construct the convex hulls of the identified sets will generally be quadratic programs with quadratic fractional constraints for which there exists no standard solution method.

Remark 4.6 (Informative and Uninformative Sharp Identified Sets)**.** For any $j \in \mathcal{J} \setminus \{f, pr\}$, we can partition $\lambda(\theta_{ij})$ into $\lambda_1(\theta_{ij})$ and $\lambda_2(\theta_{ij})$, where $\lambda_2(\theta_{ij})$ denotes the subvector of parameters listed in Result 2. of Theorem 3 and $\lambda_1(\theta_{ij})$ denotes the subvector containing the remaining components. For the components of $\lambda_1(\theta_{ij})$, the associated $\mathcal{S}_f$-sharp identified sets presented in Table 1 are informative if and only if the relevant $\mathcal{S}_f$-sharp identified sets on δ_{ij} or γ_{ij} are informative. For the components of $\lambda_2(\theta_{ij})$, the closure of the sharp identified set is either unbounded or uninformative.

The following corollary provides a general approach for obtaining $\mathcal{S}_f$-sharp identified sets on functions of components of $\beta(\theta_{ij})$ and $\lambda(\theta_{ij})$ across distinct schemes.

Corollary 3.1. *Suppose individual i satisfies Assumption 1. Consider $j_1, \ldots, j_L \in \mathcal{J} \setminus \{f, pr\}$, $j_\ell \neq j_{\ell'}$ for any $\ell \neq \ell'$. For all $\ell = 1, \ldots, L$, let τ_{ij_ℓ} denote a component of $(\beta(\theta_{ij_\ell}), \lambda(\theta_{ij_\ell}))$ and denote the $\mathcal{S}_f$-sharp identified set for τ_{ij_ℓ} as $[\tau_{ij_\ell,l}, \tau_{ij_\ell,u}]$, as constructed in Result 2. of Theorem 2 and Result 1. of*

Theorem 3. Given any function $g : \mathbb{R}^L \to \mathbb{R}$, define

$$\mathcal{G}_{i,(j_1,\dots,j_L)}(\tau_{ij_1},\dots,\tau_{ij_L}) \equiv \left\{ g(x_1,\dots,x_L) \;\middle|\; x_\ell \in [\tau_{ij_\ell,l}, \tau_{ij_\ell,u}] \;\forall\; \ell = 1,\dots,L \right\}. \tag{32}$$

Then $\mathcal{G}_{i,(j_1,\dots,j_L)}(\tau_{ij_1},\dots,\tau_{ij_L})$ is the $\mathcal{S}_f$-sharp identified set for $g(\tau_{ij_1},\dots,\tau_{ij_L})$.

In our application, we use Corollary 3.1 to construct bounds on (1) the difference in perceived probabilities of winning past and future tournaments; (2) measures of overconfidence defined as indicators for perceived probabilities of winning exceeding the objective probabilities; and (3) averages of target parameters across multiple past tournament schemes. In Appendix A we show how these three examples are covered as special cases of Corollary 3.1.

It is not possible to obtain meaningful conclusions regarding the cross-group differences in the expected value of parameters that are always unbounded or uninformative. Likewise, for any two such parameters defined for different schemes, the sharp identified set on their difference will be unbounded or uninformative, and it will not be possible to obtain meaningful conclusions on how the difference varies across groups. Thus, based on Remark 4.6, it is natural for us to exclude individual components of $\lambda_2(\theta_{ij})$ when examining how parameters or differences in parameters vary across groups.

4.3 Experimental design

Our results have important implications for the design of experiments that yield bounded and informative identified sets. Consider constructing an experimental design $\mathcal{V}$ that satisfies the following condition:

($\mathcal{V}$-1) For each $j \in \mathcal{J} \setminus \{f, pr\}$, $(j, f) \in \mathcal{S}$ and there exists $p_1, p_2 \in P_{j,f}$ such that equation (25) holds for $p = p_1, p_2$, and such that equation (31) holds.

Using Remark 3.5 and Remark 4.2, any experimental design satisfying ($\mathcal{V}$-1) results in the identified set on $V_j(p; \theta_{ij})$ from equation (24) and the $\mathcal{S}_f$-identified sets on elements of $\beta(\theta_{ij})$ for all $j \in \mathcal{J} \setminus \{f, pr\}$ being bounded and informative w.p.1, which in turn implies that the identified sets on many other target parameters are bounded and informative w.p.1 by Theorem 3 and Corollary 3.1. Following Remark 4.3, one may additionally wish to choose $|P_{j,f}| \geq 3$ for some j in order for risk neutrality to imply testable restrictions.

We now consider conditions under which ($\mathcal{V}$-1) will hold. Consider some $j \in \mathcal{J} \setminus \{f, pr\}$, and suppose $(j, f) \in \mathcal{S}$. Recall that $Q_{j,f,p}$ was defined by equation (20). Let $\{q_1, ..., q_K\} = Q_{j,f,p}$, where $q_1 \leq \cdots \leq q_K$ and for ease of exposition we suppose that $Q_{j,f,p}$ does not depend on p. Supposing that $K \geq 2$, equation

(25) can be rewritten as

$$P[q_1 < V_j(p;\theta_{ij}) < q_K] = 1, \tag{33}$$

while equation (31) can be rewritten as

$$\max_{k=1,\ldots,K-1} |q_{k+1} - q_k| < \frac{p_2 - p_1}{2}. \tag{34}$$

In this case, ($\mathcal{V}$-1) can be restated as: for each $j \in \mathcal{J} \setminus \{f, pr\}$, $(j,f) \in \mathcal{S}$, there exists $p_1, p_2 \in P_{j,f}$ such that equation (33) holds for $p = p_1, p_2$, and such that (34) holds. Equation (33) becomes more plausible the smaller q_1 and the larger q_K. However, the smaller q_1 is and the larger q_K is, the larger must be K for equation (34) to hold. For instance, equation (34) requires[6]

$$K \geq \left\lceil 2\left(\frac{q_K - q_1}{p_2 - p_1}\right)\right\rceil. \tag{35}$$

This analysis emphasizes the importance of including many choices as part of the experimental design, in particular, for each scheme $j \in \mathcal{J} \setminus \{f, pr\}$, eliciting choices between (j,p) and (f,q) for at least two (preferably at least three) values of p and for any such p eliciting the choices for many values of q. However if j involves a task performance, it may create some incentives for individuals to hedge across tasks, and it may not be feasible in practice for individuals to perform so many additional tasks as part of the experiment. It also might not be financially feasible to compensate subjects for so many tasks. As an alternative, the experiment could elicit stated preferences with no actual tasks being performed or compensated. However, individuals would then have no incentive to state their true preferences. A mechanism that finesses this tension is to have subjects state preferences for a set of choices knowing that the experimenter will later randomly implement one of their stated choices. Azrieli, Chambers, and Healy (2018) show that this mechanism is incentive compatible under even weaker conditions than the mechanism that implements all choices. This random incentive mechanism is often coupled with the multiple price lists (MPLs) method to elicit preferences (Andersen, Harrison, Lau, and Rutström, 2006).[7]

Remark 4.7 (Eliciting Choices via MPLs)**.** Applied to our setting, an MPL comparing (j,p) to (f,q) for alternative q contains two K-dimensional columns: the first column is an increasing sequence of fixed pay

[6]Although it may be tempting to choose p_2, p_1 so that their difference is large, choosing a smaller p_1 (respectively, larger p_2) will require a smaller q_1 (respectively, larger q_K) for equation (33) to hold.

[7]MPLs are commonly used in the experimental literature and have been used to elicit risk attitudes (Holt and Laury, 2002), discount rate (Andersen, Harrison, Lau, and Rutström, 2008; Coller and Williams, 1999), joint estimation of time preferences and curvature parameters (Andreoni and Sprenger, 2011), willingness to pay for commodities (Kahneman, Knetsch, and Thaler, 1990) and willingness to pay for non-commodities such as self-control (Toussaert, 2018).

payoffs $\{q_k\}_{k=1}^K$ with $q_k < q_{k+1}$, and the second column is a constant sequence of the scheme-payoff (j, p). For each row k, individuals choose whether they prefer the fixed payoff q_k to scheme-payoff (j, p), knowing that the experimenter will later select one of the K rows at random from the MPL and implement the participant's choice for that row.

The above discussion suggests a design different from the NV design, which elicits a single choice between past tournament and piece-rate schemes and a single choice between future versions of these schemes. Although their alternative schemes are not fixed pay, following Remark 4.2, it is natural to conjecture that identified sets on δ_{ij} and γ_{ij} are uninformative under their design without additional assumptions because individuals only make a single choice between j and another scheme. The following remark establishes this conjecture, and further shows that identified sets on generalizations of these parameters are also uninformative.

Remark 4.8 (Identification under NV Design)**.** Consider the NV experimental design. In Online Appendix D, we show that without further assumptions, the sharp identified sets for δ_{ij} and γ_{ij} are unbounded or uninformative for any $j \in \mathcal{J} \setminus \{f, pr\}$. Furthermore, as long as $\delta_{ij'} \neq 0$, the sharp identified sets for $\frac{\delta_{ij}}{\delta_{ij'}}$ and $\frac{\gamma_{ij}-\gamma_{ij'}}{\delta_{ij'}}$, which are the natural generalizations of slope and intercept parameters when the alternative scheme is not fixed pay, are also respectively unbounded and uninformative for any (j, j') where either j or j' in $\mathcal{J} \setminus \{f, pr\}$.

As we show in Online Appendix D, NV are able to provide non-trivial results with their design by implicitly imposing several cross-scheme restrictions and cross-individual homogeneity restrictions. The restrictions are that $\pi_{i,ft} = \pi_{i,pt}$, that $\mu_{i,ft} = \mu_{i,pt}$, and that $\pi_{i,ft}$ and $\pi_{i,pt}$ are degenerate and equal across men and women with the same past tournament choice, past rank guess, and past score. We empirically reject these restrictions in our experiment: individuals have differing subjective beliefs about past and future tournaments, and we consistently find heterogeneity in beliefs between men and women, even conditional on past rank guess or past performance.

4.4 Estimation and inference of group-level mean parameters

Thus far we have considered individual-level bounds on parameters of interest, in particular, individual-level bounds $[L_i,\ U_i]$ on various individual-level parameters $\tau_i^\star$ for which it is possible to obtain bounded and informative partial identification. We now consider aggregating these bounds across individuals to perform inference for group-level population means (and cross-group differences in such means) of these individual-level parameters. We keep this analysis brief and defer theoretical details to Appendix B.

Recall that G_i is a discrete random variable denoting group membership like gender. Supposing that $\mathbb{E}|L_i|$, $\mathbb{E}|U_i| < \infty$, that $\tau_i^\star \in [L_i, U_i]$ w.p.1 implies that for any group g:

$$\mathbb{E}[\tau_i^\star \mid G_i = g] \in \Bigg[\mathbb{E}[L_i \mid G_i = g],\ \mathbb{E}[U_i \mid G_i = g]\Bigg], \tag{36}$$

and for any groups g, g',

$$\mathbb{E}[\tau_i^\star \mid G_i = g]-\mathbb{E}[\tau_i^\star \mid G_i = g'] \in \Bigg[\mathbb{E}[L_i \mid G_i = g]-\mathbb{E}[U_i \mid G_i = g'],\ \mathbb{E}[U_i \mid G_i = g]-\mathbb{E}[L_i \mid G_i = g']\Bigg]. \tag{37}$$

Consider estimation of the above parameters. For any group g, let $\bar{L}_g$ and $\bar{U}_g$ denote the sample means of L_i and U_i, respectively, conditional on $G_i = g$. We estimate the population mean bounds in (36) and (37) using their respective sample analogues: $[\bar{L}_g,\ \bar{U}_g]$ and $[\bar{L}_g - \bar{U}_{g'},\ \bar{U}_g - \bar{L}_{g'}]$. Supposing i.i.d sampling, the sample analog's lower and upper bounds are consistent estimators of the population lower and upper bounds assuming that $\mathbb{E}|L_i|, \mathbb{E}|U_i| < \infty$, $\Pr[G_g = g] > 0$ and $\Pr[G_g = g'] > 0$.

For inference on the above parameters, we implement the confidence intervals proposed in Imbens and Manski (2004). In Appendix B, we give details on the CIs and use the results of Imbens and Manski (2004), Stoye (2009) and Bhattacharya, Shaikh, and Vytlacil (2012) to establish that the CIs have desirable properties (are uniformly consistent in level) under weak conditions in our context. With L_i and U_i random variables that take only a finite number of values, the conditions require only that $L_i \leq U_i$ w.p.1, that $\Pr[G_i = g]$ and $\Pr[G_i = g']$ are bounded away from zero, and that the conditional probabilities that L_i and U_i equal any given value is bounded away from one. The results of Appendix B may be of interest outside of our context whenever applying the confidence intervals proposed in Imbens and Manski (2004) to bounds for which the upper and lower endpoints are conditional means of discrete random variables.

Remark 4.9 (When Individual-Level Identified Sets are not Bounded w.p.1)**.** Suppose that equation (33) is violated, so that with positive probability either $D_{j,f}(p, q; i) = 0$ for all $q \in Q_{j,f,p}$, or $D_{j,f}(p, q_k; i) = 1$ for all $q \in Q_{j,f,p}$, and thus identified sets for $V_j(p; \theta_{ij})$ are unbounded with positive probability. In that case, it is possible for identified sets for $\tau_i^\star$ to be unbounded with positive probability, which would imply that the identified set for the population mean of $\tau_i^\star$ is unbounded. In order to avoid unbounded identified sets for the aggregate parameter, one could redefine the aggregate parameter to be the expectation of $\tau_i^\star$

conditional on some event B_i that ensures that the corresponding identified set is bounded. One could then follow the previous analysis to estimate this aggregate parameter by group, and the differences in the parameter across groups, using the sample of individuals with $B_i = 1$. We take B_i to be the indicator that the identified set for $\tau_i^\star$ is bounded. To ensure that identified sets for multiple parameters are jointly bounded, it suffices to take B_i to be the intersection of indicators for each identified set being bounded. Note that the inference results of Appendix B with straightforward extensions nest this case with the added assumption that $Pr[B_i = 1]$ is bounded away from zero uniformly.

5 Empirical application

We apply our methodology to analyze the role of gender in self-selection into competitive compensation schemes. We discuss our experimental design in Subsection 5.1 and present descriptive statistics for our experiment in Subsection 5.2. We compare payoff indifference sets by gender in Subsection 5.3 and find that, relative to women, men consistently prefer tournament tasks. This gender gap widens when schemes are applied to future tasks. These findings are consistent with that of Niederle and Vesterlund (2007). In Section 6, we use our model of selection to determine what drives these gender gaps.

5.1 Experimental design and implementation

Our experimental design is built on that of Niederle and Vesterlund (2007) with judicious modifications. These modifications are based on both the application of our theoretical results and the practical limitations of those results discussed in Section 4. We now briefly discuss our design. Further details can be found in Online Appendices H and I.

Experiment design. We follow the NV design and ask participants to add up sets of five 2-digit numbers in a series of addition tasks during the experiment. We similarly ask participants to choose between pairs of scheme-payoffs that they'd like to apply to these tasks, with the choices elicited in a manner that incentivizes truthful revelation. As in the NV design, we also elicit past performance, past tournament rank guess, and gender.

We make three key modifications to the NV design for the purposes of identifying parameters of interest. First, we expand the set of compensation schemes to include fixed pay and future lumpsum schemes. Second, for each considered compensation scheme, we elicit choices between that scheme and fixed pay at three base-payoffs. Eliciting choices at three base-payoffs allows us to additionally test an empirical implication of risk neutrality following Remark 4.3. Finally, following Remark 4.7, we elicit choices using the Multiple Price List (MPL) method.[8] For each MPL, participants are presented two columns: the first column (Option A) is a sequence of scheme-payoffs with ascending payoffs, and the second column (Option B) is a constant sequence of a scheme-payoff. For each row of the MPL, individuals choose whether they prefer to apply Option A or Option B to their relevant performance, knowing that the experimenter may later select one row at random from the MPL and implement the participant's choice. When designing the ascending sequences of Option A payoffs for each MPL, we are mindful of the tension between the theory suggesting having many payoffs that span a wide interval and practical concerns suggesting having fewer payoffs that span a smaller interval to limit the total number of choices made by individuals and to ensure budget-feasibility.

Two other aspects of our experimental design warrant a brief discussion. First, we follow NV in eliciting choices between future tournament and future piece-rate compensation schemes, allowing us to examine whether these choices elicited in the same manner as NV are consistent with those elicited using MPLs between either scheme and fixed pay. We discuss these consistency checks in greater detail in Subsection 6.1. Second, we elicit choices for three past tournament and three past piece-rate schemes instead of just one of each.[9]

Experiment flow. Each experiment consists of four parts. Part one contains practice rounds for both addition tasks and MPLs. In part two, participants perform three piece-rate addition tasks and three tournament addition tasks. After each tournament addition task, participants are asked to fill out MPLs to be applied to these past tournament tasks. MPLs in this part ask participants to make choices between each past tournament at three distinct base-payoffs versus fixed pay.[10] We notify participants about these base-payoffs before the start of each relevant addition task, and notify participants about their relevant past performances when completing the MPLs. In part three, participants do not perform any addition tasks but instead fill out MPLs to be applied to a future addition task. Participants are told that if

[8]An alternative mechanism to elicit valuations is the Becker-DeGroot-Marshak (BDM) mechanism. Some studies have found that, in practice, individuals may sometimes misunderstand the BDM mechanism and report values that do not equate to their true valuations (Bull, Courty, Doyon, and Rondeau, 2019; Cason and Plott, 2014; Holt and Smith, 2016). This practical concern motivated our use of MPLs instead of the BDM mechanism. Replication of our results using the BDM mechanism is left for future research.

[9]For ease of notation, we considered a single past tournament scheme and a single past piece-rate scheme in our theoretical analysis. The analysis of Sections 3 and 4 immediately extends to a setting with multiple past tournaments and multiple past piece-rate schemes.

[10]For tournament or piece-rate schemes, the base-payoff is the payment per correct answer (conditional on winning in case the case of tournament). In this experiment the base-payoffs for piece rate are: \$0.8, \$1.6, and \$2.4, and for tournament are: \$3.2, \$6.4, and \$9.6.

one row of an MPL in this part is selected for payment, they will subsequently perform a three minute addition task and be compensated given the choice they made in the selected row. In the last part of the experiment, we elicit participants' risk preferences following Holt and Laury (2002) and rank guess about their past performances following Niederle and Vesterlund (2007).[11] Finally, compensation is determined. If the compensation requires that the participant performs a future task, participants perform the task.

Compensation. Prior to the start of the experiment, participants are told that a randomization device will choose either an addition task from part 2, a MPL from part 2, or a MPL from part 3 to determine compensation. If an addition task is chosen for payment, participants will be paid according to the task type and their performance. If a MPL is chosen for payment, a random row will be chosen from that MPL and the choice made by the participants in that row will be implemented. This randomization process provides incentive for participants to be truth-telling in choices they make (Azrieli, Chambers, and Healy, 2018; Freeman, Halevy, and Kneeland, 2019).

Group assignment for competitive pay schemes. At the start of the experiment, participants are randomly assigned into groups of four. In all competitive compensation schemes, regardless of whether it is for a past or future performance, participants are told that they will be competing against the past performances of three randomly selected members in the experiment. This controls the effect of perceptions about the selection decisions of others (Niederle and Vesterlund, 2007).

5.2 Data and descriptive statistics

The experiment was conducted between October 2019 to March 2020 at Yale University's Behavioral Research Lab (BRL).[12] Undergraduate students were recruited using standard recruiting procedures by the BRL, including sending email invitations to the subject pool maintained by the BRL and advertising on the university's interactive teaching platform. We recruited 176 participants in total. In addition to knowing the gender of participants, we also elicited the participants' age, major, and GPA. Since the main objective of our experiment is to understand differences by gender, we dropped three participants who identified as non-binary. Of the remaining 173 participants, 103 (60%) were female.[13] The average age of participants was 21, and the median was 20. Among participants, 16% were pursuing economics

[11]For all rank guesses, individuals are paid 50 cents per correct rank guess.

[12]The experiment was approved by the Institutional Review Board of Yale University.

[13]The BRL's total subject pool is about 62% female. The overrepresentation of women is common in lab experiments conducted on university campuses.

majors, 33% were pursuing STEM majors, and another 25% were pursuing political science, history, and sociology majors. We conducted 19 sessions with an average of 9 participants per session. Each session lasted about an hour and fifteen minutes. Participants received an average total compensation of $30.

We further restrict our sample by dropping individuals who exhibited behavior indicative of not complying with our experiment or not understanding the MPL format. In particular, we drop one individual who did not complete the addition tasks, and twenty-five individuals who either left blank or switched multiple times on MPLs that elicited choices between fixed pay and competitive schemes.[14] There is no gender discrepancy in the share of such individuals. Our baseline sample thus consists of 147 participants, of which 84 (57%) were female. In this sample, we find that the average score on the addition tasks is 8.4 for men and 7.3 for women, and this difference is significant at the 0.05 level.[15] This gender difference in performance is consistent with the findings of other studies, including Niederle and Vesterlund (2007). Although Niederle and Vesterlund (2007) find a statistically insignificant difference, larger studies often find the difference to be statistically significant (see, e.g., Almås, Cappelen, Salvanes, Sørensen, and Tungodden (2016); Buser, Niederle, and Oosterbeek (2014); Price (2012); Balafoutas, Fornwagner, and Sutter (2018)).

5.3 Payoff indifference sets

We begin by examining payoff indifference sets by gender.[16] Following Remark 4.9, we condition our baseline sample on individuals who switch from choosing the constant scheme-payoff to the alternative scheme with varying base-payoffs at some row of the relevant MPL and thus have bounded payoff indifference sets. Only 4% of payoff indifference sets are unbounded. Online Appendix Table A.2 presents, by gender and pair of schemes, the frequency of payoff indifference sets that are bounded, unbounded above, and unbounded below. We find that men are more likely to have unbounded payoff indifference sets and are substantially more likely to have these sets be unbounded above.[17]

Figure 1 presents estimated mean payoff indifference sets of tournament schemes relative to piece-rate

[14] The presence of multiple-switchers is a common phenomenon in lab experiments using MPLs and may reflect poor quality of decision making (Yu, Zhang, and Zuo, 2020).

[15] Online Appendix Table A.1 presents performances by compensation scheme (piece rate or tournament), base-payoff, and gender.

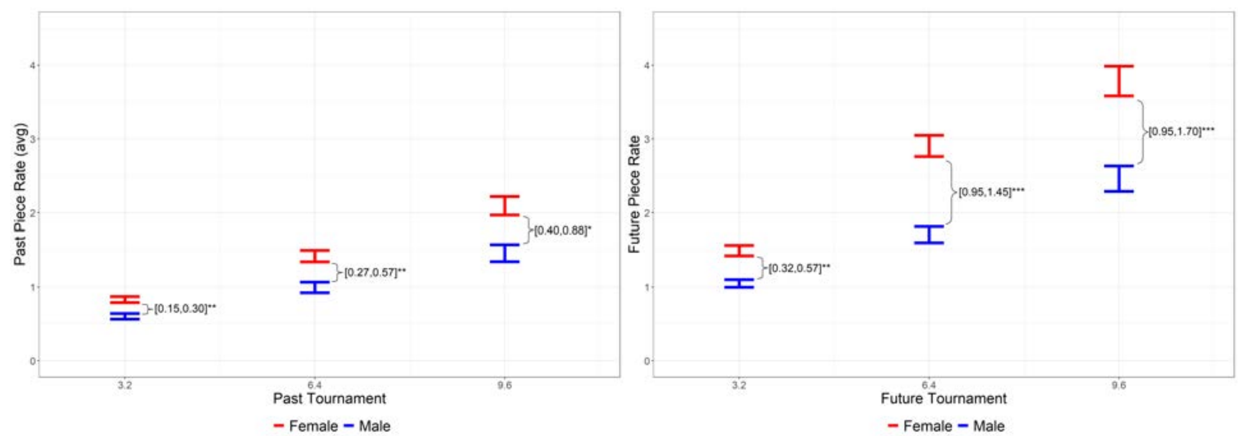
[16] If individuals make choices based on maximizing expected utility, and expected utility is strictly increasing in base-payoff, then payoff indifference sets are identified sets for the value at which the individual is indifferent between the scheme-payoff and the alternative scheme with base-payoff at that value. These payoff indifference sets can thus be interpreted under weaker conditions than Assumption 1.

[17] Given this finding, a potential concern with conditioning on bounded payoff indifference sets is that it may unequally truncate the distributions of valuations by gender. Because men are substantially more likely to have valuations that are unbounded from above while women are more likely to have valuations that are unbounded from below, our results may understate the gender gap.

schemes by gender. For each tournament payoff (x-axis), we depict mean payoff indifference sets in blue for men and in red for women, with bounds on the gender difference presented alongside in brackets. Panel (a) reports these sets for past tournament relative to past piece rate, while Panel (b) reports them for future tournament relative to future piece rate.[18] We find that men value tournaments relative to piece-rate compensation more than women at all base-payoffs, and this gender gap is higher for future tasks than for past tasks. The figure also shows that the difference in valuation for tournament versus piece rate is higher on average for future tasks than for past tasks for both genders.

Figure 1: Tournament payoff indifference sets relative to piece rate

(a) Past Tournament vs Past Piece Rate (b) Future Tournament vs Future Piece Rate



Notes: *p<0.1; **p<0.05; ***p<0.01. Sample mean valuation sets are depicted in blue for men and red for women. Bounds on the difference between mean male and female valuation sets are presented by the curly brackets. For each difference, we test the null of the bounds containing zero. Sample is restricted to the baseline sample, and we further restrict to bounded payoff indifference sets.

We present mean payoff indifference sets by gender for these MPLs in table form in Online Appendix Table A.3. This table also presents payoff indifference sets by gender for MPLs where the alternative scheme is fixed pay. Compared to women, men have a greater valuation for task-based compensation schemes (competitive or noncompetitive) relative to fixed pay. We also find that the gender gap in the valuation of a tournament appears to be larger for future tournament relative to past tournament.

Our analysis of payoff indifference sets is consistent with the findings of Niederle and Vesterlund (2007) that men are more likely than women to select tournament over piece-rate compensation, and that this gender gap is larger when the schemes are applied to a future as opposed to a past task. We replicate the analysis of Niederle and Vesterlund (2007) using our sample to further investigate the similarities between our sample and theirs. Notably, a probit of future tournament entry on past performance, past

[18] Since past piece rate is equivalent to a scaled fixed pay scheme, payoff indifference sets for past tournament relative to past piece rate are constructed by taking payoff indifference sets for past tournament relative to fixed pay and dividing by the past piece-rate performance.

rank guess, and past tournament entry results in an estimated marginal gender effect of 0.17 ($p < 0.05$), which is remarkably similar to the estimated marginal effect of 0.16 of Niederle and Vesterlund (2007). Rather than attributing this gender gap to a difference in non-monetary preferences for entering a future tournament, we use our methodology to (partially) identify belief and preference parameters.

6 Empirical analysis under our model of selection

Our findings in the previous section reveal that, relative to women, men consistently prefer tournament tasks. This gender gap widens when considering future tournament tasks. In this section, we use our methodology to estimate identified sets for beliefs and non-monetary preference parameters to determine what drives these gender gaps. Subsection 6.1 assesses the validity of our model, and Subsections 6.2 and 6.3 present our main results. Overall, our results suggest that the main explanation for the gender gap in selection into future tournaments is not a gender difference in non-monetary preferences, but rather a gender difference in the subjective probability of winning a future competitive task.

6.1 Imposing our model of selection

Prior to examining identified sets for the mean belief and preference parameters, we investigate empirical evidence related to the validity of the selection model of Assumption 1. For the purposes of contextualizing our analysis, we also investigate whether the elicitation methods of the NV design and our experimental design are consistent with each other. Finally, we discuss restricting our sample to those individuals for whom we can construct bounded identified sets for all beliefs and preference parameters we consider in our upcoming analysis.

Evidence related to model validity. Our model imposes that beliefs and preferences are base-payoff invariant and that risk preferences do not influence valuations of compensation schemes. We analyze supporting evidence for these assumptions in Online Appendix E, and here summarize that evidence.

Consider elicited rank guess as a proxy for perceived performance on the corresponding past tournament. A regression of rank guess on past tournament base-payoffs and other controls reveals a small and insignificant coefficient for base-payoffs ($p = 0.69$). Now consider relative risk aversion, which we set-identify for individuals based on the Holt and Laury (2002) design. We find that individuals are slightly risk averse on average, though we fail to find a difference in mean risk aversion by gender.[19] We

[19]The absence of a gender difference in risk attitude using the Holt and Laury (2002) design is largely consistent with

also find that risk preferences do not appear to influence tournament valuations. In particular, we run regressions of valuations on number of safe choices in the Holt and Laury (2002) design–a proxy for risk aversion–and other covariates separately by tournament type and base-payoff. In each regression, the coefficient on elicited risk aversion is small and statistically insignificant, and we cannot reject the null hypothesis that the coefficients on risk aversion for these regressions are jointly equal to zero ($p = 0.98$).

We examine the testable restriction of risk neutrality described in Remark 4.3 for each individual and scheme. Only 8% of cases reject the testable restriction, and there is no appreciable gender difference in the share of cases that reject the restriction.[20]

Consistency between elicitation methods. The NV design elicits a single choice between a past tournament scheme at a base-payoff of \$2 and a piece-rate scheme at a base-payoff of 50 cents, and a single choice between future tournament and piece-rate schemes at these same base-payoffs. In contrast, our analysis uses MPLs including MPL-elicited choices between these schemes and fixed pay. We exploit that our experimental design includes both elicitation methods to examine consistency between them.

Online Appendix F describes the consistency checks we perform. In 90% of cases, NV's approach and the MPL approach of eliciting choices between tournament and piece-rate schemes are consistent with each other. In 84% of cases, MPL-elicited choices between tournament and piece-rate schemes are consistent with MPL-elicited choices between these schemes and fixed pay. These shares are similar by gender. Coupled with our near-exact replication of the main result of Niederle and Vesterlund (2007) using their methods on our data, these results suggest that differences in our conclusions from Niederle and Vesterlund (2007) follow from our alternative methodology and not from our differing experimental samples or choice of elicitation methods.

Restricting to a model sample. We focus on analyzing belief and preference parameters for competitive compensation schemes, and, in particular, for $j = pt$ (average past tournament as defined in Appendix A), $j = ft$ (future tournament), and $j = fl$ (future lumpsum tournament). We do so by first restricting our sample to those individuals i for whom the programs for constructing the identified sets for δ_{ij} and γ_{ij} for our considered schemes are feasible. Doing so removes thirty-three individuals, and there is no gender discrepancy in the share of such individuals. We henceforth restrict our analysis to the resulting sample of 114 individuals, of which 68 (60%) are female. We denote this sample as the model

the literature (Filippin and Crosetto, 2016).

[20] See Online Appendix Table E.4 for the share of cases that reject the restriction by scheme and gender.

sample.[21] Following Remark 4.9, we further restrict our analysis to those individuals with bounded identified sets for all considered parameters, resulting in a sample of 103 individuals, of which 67 (65%) are female. Of the eleven individuals in the model sample who have at least one unbounded identified set, ten are men. Examining whether these unbounded identified sets are due to payoff indifference sets that are unbounded below or above, we find that they are unbounded above for all ten men, and unbounded below for the single woman.[22]

6.2 Expected value of beliefs and non-monetary preference parameters

In this subsection, we investigate the expected value of individual-level belief and non-monetary preference parameters conditional on gender. We first review the relevant individual-level parameters and relate them to the terminology we use in the upcoming empirical analysis. Notation for the expected value of these parameters is presented in parentheses.

Beginning with performance-related beliefs, we compare individuals' subjective probabilities of winning past and future tournaments. Since individuals perform three past tournament tasks, we consider individuals' subjective probability of winning averaged over these three past tasks and refer to this average as the individual's past subjective probability of winning (π_{pt}). While we cannot construct informative identified sets on the subjective probability of winning a future tournament, we can on the subjective probability of winning a future lumpsum tournament. We suspect that these subjective probabilities are equal since they have the same condition for winning.[23] We thus refer to this value as the future subjective probability of winning (π_{fl}). We examine how the future and past subjective probabilities of winning compare by constructing identified sets on the difference of these values ($\pi_{fl} - \pi_{pt}$).

We also compare subjective beliefs to objective performance. An individual wins a past tournament task if their score for the task is weakly higher than the past performance of three other randomly-selected participants, and thus we compute an individual's objective probability of winning that task given their realized score in the task by cubing the full sample CDF of past performances evaluated at their realized score. An individual may have distinct realized scores, and thus distinct objective probabilities of winning

[21] Online Appendix Table A.4 presents task scores for this model sample, while Online Appendix Table A.5 presents mean payoff indifference sets for individuals in the model sample with bounded payoff indifference sets. Online Appendix Figure A.1 replicates Figure 1 for individuals in the model sample with bounded payoff indifference sets. The conclusions are similar to those in Section 5.

[22] Given this finding, a potential concern with conditioning on bounded identified sets for all our considered parameters is that it may unequally truncate the distributions of these parameters by gender. Because the men have unbounded identified sets due to payoff indifference sets that are unbounded above while the woman has unbounded identified sets due to payoff indifference sets that are unbounded below, our results may understate the gender gaps in beliefs and preferences.

[23] The only difference is the compensation conditional on winning: a future tournament offers the payoff multiplied by the realized performance whereas a future lumpsum tournament offers the payoff and thus does not depend on performance.

given their realized scores, for each of the three past tournament tasks. We thus consider an individual's objective probability of winning averaged over their three past tournament tasks and refer to this average as the individual's objective probability of winning ($\pi^\star$).

We also consider non-monetary preferences. For each past tournament, expected non-monetary preferences correspond to the expected value of feedback aversion. As above, we consider the average of these parameters across the three past tournament tasks, which we denote as the past tournament non-monetary preference (ψ_{pt}). While we cannot construct bounded and informative identified sets for the cost of entering a future tournament, we can construct such sets for the expected non-monetary preferences for future tournament, which we denote as the future tournament non-monetary preference ($\psi_{ft} + c_{ft}$). As the notation suggests, this value corresponds to the sum of expected values of feedback aversion and cost of performing a future tournament task.

The individual identified sets that we aggregate are explicitly defined in Online Appendix Table G.1.[24] We construct asymptotic 95% confidence intervals on the expected values of these parameters following the analysis of Appendix B.

6.2.1 Analysis by gender

Table 2 reports estimated identified sets and asymptotic 95% confidence intervals for the expected value of tournament performance-related belief and preference parameters conditional on gender, and for the cross-gender difference in these conditional expectations. In the following, we focus our discussion on the 95% asymptotic confidence intervals, and all statements of statistical significance are at the corresponding 0.05 nominal level.

From Panel A, we cannot reject the null hypothesis that men and women have the same average subjective probability of winning a past tournament. In contrast, we reject the null for a future tournament, with the 95% CI implying that men are eight to twenty-nine percentage points more confident on average. Examining the results in Panel B, the relevant 95% CI implies that men on average are at least eight percentage points (and as high as twenty-eight percentage points) more confident in their future than past chance of winning. In contrast, we cannot reject the null hypothesis that women are equally confident in their subjective probability of winning a future versus past tournament. Comparing perceived to objective probability of winning tournaments, the CIs imply that women (but not necessarily men)

[24] All individual identified sets correspond to δ_{ij} and γ_{ij} for some j or functions of these parameters which are constructed following the Examples in Appendix A. We construct identified sets for these parameters by solving programs following Remark 4.4. Programs are solved with Gurobi Optimization (2020).

are overly pessimistic about their chances of winning a past tournament, while men (but not necessarily women) are overly optimistic about their chances of winning a future tournament. While Panels A and B of Table 2 report results for perceived probability of winning tournaments, Online Appendix Table A.6 reports the analogous results for anticipated tournament earnings. We find that men expect higher earnings from future tournaments than women on average and this difference is statistically significant, while we cannot reject the null hypothesis that men and women have equal average expected earnings from past tournaments.

Panel C provides results for the expected non-monetary value of a tournament task, which is the value of feedback for a past tournament and the sum of the value of feedback and the preference for performing the task in a competition for a future tournament. The corresponding 95% CIs for men includes zero for both past and future tournaments. In contrast, the corresponding CIs for women are strictly positive for both past and future tournaments, indicating that women on average place positive value on the feedback from a past tournament and on the sum of that value and the preference for performing the task in a competitive environment for a future tournament.

In summary, the results in Table 2 suggest that men are far more confident than women in their probability of winning a future (though not necessarily a past) tournament. The results emphasize that individuals, especially men, have different beliefs about performance for future versus past tournaments, and that their beliefs do not correspond on average to objective measures. Our results on preferences contrast with the previous literature: we find that women place positive non-monetary value on participating in a tournament, and we are unable to reject that men and women have the same average non-monetary preferences for competing. These results thus suggest that it is beliefs and not necessarily preferences that explain men having a greater tendency than women to enter future tournaments.

6.2.2 Analysis by gender and performance level

Table 3 replicates the results from Table 2 by performance level, where we classify individuals as high or low performing based on whether their objective probability of winning (given their realized performance) averaged over the three past tournament tasks is weakly greater than one-fourth.[25] Individuals typically perform similarly in the three past tournament tasks, with the average individual-specific variance in performance equaling 2.25. In contrast, the cross-person variance in average performance is more than

[25] Since individuals compete in groups of four, if task performances were random draws from the same distribution and if we ignored ties arising from the discrete nature of performances, each individual would have a 25% chance of winning.

Table 2: Beliefs and preferences

No.	Parameter	Description	Male	Female	Male - Female
Panel A: tournament beliefs					
(1)	π^*	Objective	0.27	0.23	0.04
		probability of winning	(0.18,0.36)	(0.17,0.28)	(-0.06,0.15)
(2)	π_{pt}	Past subjective	[0.18,0.23]	[0.10,0.14]	[0.04,0.13]
		probability of winning	(0.13,0.28)	(0.07,0.17)	(-0.02,0.19)
(3)	π_{fl}	Future subjective	[0.36,0.40]	[0.17,0.22]	[0.14,0.23]
		probability of winning	(0.31,0.46)	(0.14,0.26)	(0.08,0.29)
Panel B: differences in tournament beliefs					
(4)	$\pi_{pt} - \pi^*$	Past subjective - objective	[-0.09,-0.04]	[-0.13,-0.09]	[-0.01,0.09]
		probability of winning	(-0.17,0.04)	(-0.18,-0.04)	(-0.10,0.18)
(5)	$\pi_{fl} - \pi^*$	Future subjective - objective	[0.09,0.13]	[-0.05,-0.01]	[0.10,0.18]
		probability of winning	(0.01,0.21)	(-0.10,0.04)	(0.00,0.28)
(6)	$\pi_{fl} - \pi_{pt}$	Future subjective - past subjective	[0.13,0.23]	[0.03,0.12]	[0.01,0.19]
		probability of winning	(0.08,0.28)	(-0.00,0.16)	(-0.05,0.25)
Panel C: non-monetary preferences					
(7)	ψ_{pt}	Past tournament	[-0.01,1.73]	[0.98,2.91]	[-2.92,0.75]
		non-monetary preference	(-1.01,2.73)	(0.38,3.82)	(-4.27,1.92)
(8)	$\psi_{ft} + c_{ft}$	Future tournament	[0.88,2.91]	[1.41,2.64]	[-1.76,1.50]
		non-monetary preference	(-0.12,3.89)	(0.92,3.17)	(-2.89,2.59)

Notes: This table presents mean estimated identified sets (in brackets) and 95% CIs (in parentheses) for belief and preference parameters by gender and for the difference between men and women. Notation follows that of Subsection 6.2 and identified sets for parameters are explicitly defined in Online Appendix Table G.1. Sample is restricted to those individuals in the model sample with bounded identified sets for all parameters considered in this section.

2.5 times as large at 5.71.[26] This finding motivates our classification of individuals as high or low performing. We document four key takeaways.[27]

First, for both low and high performing individuals, we find that men have a higher average subjective-net-of-objective probability of winning a future (but not necessarily a past) tournament compared to women. Thus, the cross-gender differences in perceived chances of winning a tournament that we found in Table 2 holds within both low and high performing subgroups. In Online Appendix Figures A.2 and A.3 we show that differences in these beliefs between men and women persist conditional on past performance

[26]A similar result emerges comparing the average individual-specific variance in objective probability of winning (0.02) and the cross-person variance in average objective probability of winning (0.06).

[27]While Panels A and B of Table 3 report results for perceived probability of winning tournaments, Online Appendix Table A.7 reports the analogous results for anticipated tournament earnings. The CIs for anticipated earnings conditional on gender and performance tend to be wide and uninformative.

and on past rank guess. Taken together, these results reject the implicit assumption of homogeneity in beliefs required in NV's analysis (see Subsection 4.3).

Second, the results from Table 2 that women on average are overly pessimistic about their chances of winning a past tournament and men on average are overly optimistic about their chances of winning a future tournament appear to be driven by high performing women being overly pessimistic and low performing men being overly optimistic. Comparing average perceived probabilities of winning a tournament to the objective probabilities, we find that low—but not high—performing men are overly confident in their chances of winning a past tournament and vastly overconfident for future tournaments. We find that, on average, high—but not low—performing women are overly pessimistic about their chances of winning a future tournament and vastly overpessimistic for past tournaments.

Third, low performing men have beliefs that exceed or are comparable to high performing women. The estimated identified set on subjective probability of winning a future tournament for low performing men is not only strictly above that of low performing women, it is also strictly above that of high performing women. This is despite the fact that the objective probability of winning for low performing men is 38 percentage points lower than that of high performing women. In additional analysis, we find that the 95% CI on the difference in average subjective probability of winning a future tournament between low performing men and high performing women is $(-0.051, 0.224)$, so that not only do we fail to reject the null hypothesis of equal beliefs, we also cannot reject the null hypothesis that low performing men are 22 percentage points more confident of success in future tournaments than are high performing women.

Finally, we find that high performing women place positive non-monetary value on participating in both past and future tournaments, and that low performing women do so for future (though not necessarily for past) tournaments. In contrast, we cannot reject the null hypothesis for both low and high performing men that their non-monetary value of participating in either a past or future tournament is zero.

In summary, the results from Table 2 largely hold conditional on performance level, though with evidence that low performing men are driving much of the overconfidence of men for future tournaments while high performing women are driving much of the under-confidence of women for past tournaments. We again find evidence that women (especially high performing women) on average enjoy participating in tournaments without finding corresponding evidence for men.

Table 3: Beliefs and preferences, by performance

No.	Parameter	Description	Low Performance Male	Low Performance Female	Low Performance Male - Female	High Performance Male	High Performance Female	High Performance Male - Female
Panel A: tournament beliefs								
(1)	π^*	Objective	0.09	0.10	-0.01	0.56	0.47	0.09
		probability of winning	(0.05,0.13)	(0.08,0.12)	(-0.06,0.03)	(0.44,0.68)	(0.40,0.55)	(-0.05,0.22)
(2)	π_{pt}	Past subjective	[0.15,0.20]	[0.09,0.14]	[0.01,0.11]	[0.22,0.26]	[0.10,0.15]	[0.07,0.16]
		probability of winning	(0.09,0.27)	(0.06,0.17)	(-0.05,0.19)	(0.15,0.35)	(0.06,0.20)	(-0.02,0.25)
(3)	π_{fl}	Future subjective	[0.32,0.37]	[0.14,0.18]	[0.14,0.23]	[0.41,0.46]	[0.24,0.28]	[0.13,0.22]
		probability of winning	(0.27,0.43)	(0.10,0.23)	(0.07,0.30)	(0.32,0.55)	(0.17,0.36)	(0.02,0.34)
Panel B: differences in tournament beliefs								
(4)	$\pi_{pt} - \pi^*$	Past subjective - objective	[0.06,0.12]	[-0.01,0.04]	[0.02,0.12]	[-0.34,-0.29]	[-0.37,-0.32]	[-0.02,0.07]
		probability of winning	(0.00,0.19)	(-0.05,0.08)	(-0.05,0.20)	(-0.44,-0.19)	(-0.43,-0.25)	(-0.14,0.19)
(5)	$\pi_{fl} - \pi^*$	Future subjective - objective	[0.24,0.28]	[0.04,0.08]	[0.15,0.24]	[-0.15,-0.10]	[-0.23,-0.19]	[0.04,0.14]
		probability of winning	(0.18,0.35)	(-0.01,0.13)	(0.08,0.32)	(-0.27,0.03)	(-0.32,-0.10)	(-0.10,0.28)
(6)	$\pi_{fl} - \pi_{pt}$	Future subjective - past subjective	[0.12,0.22]	[0.01,0.09]	[0.03,0.21]	[0.15,0.24]	[0.09,0.18]	[-0.03,0.15]
		probability of winning	(0.05,0.29)	(-0.03,0.13)	(-0.05,0.30)	(0.08,0.31)	(0.03,0.24)	(-0.13,0.24)
Panel C: non-monetary preferences								
(7)	ψ_{pt}	Past tournament	[0.73,2.16]	[0.11,1.39]	[-0.66,2.05]	[-1.18,1.05]	[2.63,5.81]	[-6.99,-1.58]
		non-monetary preference	(-0.03,2.81)	(-0.37,1.89)	(-1.57,2.86)	(-3.40,3.46)	(1.31,7.99)	(-10.10,1.16)
(8)	$\psi_{ft} + c_{ft}$	Future tournament	[0.68,2.39]	[0.74,1.88]	[-1.20,1.65]	[1.20,3.73]	[2.70,4.10]	[-2.90,1.03]
		non-monetary preference	(-0.22,3.31)	(0.22,2.41)	(-2.24,2.70)	(-1.00,5.79)	(1.82,5.09)	(-5.31,3.27)

Notes: This table presents mean estimated identified sets (in brackets) and 95% CIs (in parentheses) for belief and preference parameters by gender and for the difference between men and women, by performance status. An individual is high performance if their objective probability of winning is greater than or equal to 25%, and is otherwise low performance. Notation follows that of Subsection 6.2 and identified sets for parameters are explicitly defined in Online Appendix Table G.1. Sample is restricted to those individuals in the model sample with bounded identified sets for all parameters considered in this section.

6.3 Indicator target parameters

Thus far, we have examined conditional expected values of belief and preference parameters. We found, for example, that men on average are overconfident in their chances of winning a future tournament. That analysis does not directly address the question of what fraction of men are overconfident. We now address such questions by applying Corollary 3.1.[28] We are able to do so by exploiting that we set-identify the belief and preference parameters at the individual-level.

We address such questions for three underlying individual-level parameters: the objective probability of winning a tournament, the subjective probability of winning a past tournament, and the subjective probability of winning a future tournament. For each pair of these individual-level parameters, we consider the probability that one parameter is strictly greater than another conditional on gender (in Subsection 6.3.1) or conditional on gender and performance level (in Subsection 6.3.2). The individual identified sets that we aggregate are explicitly defined in Online Appendix Table G.2.[29] As in Subsection 6.2, we focus

[28]See Example A.2 of Appendix A for how this analysis follows from Corollary 3.1.

[29]See also Example A.2 of Appendix A. For details on how we construct asymptotic 95% confidence intervals on these conditional probabilities, see Example B.3 of Appendix B.

our discussion on the 95% asymptotic confidence intervals, and all statements of statistical significance are at the corresponding 0.05 nominal level.

6.3.1 Analysis by gender

Table 4 reports, for each pair of listed underlying parameters, the estimated identified set and 95% confidence interval for the probability that the first parameter does not equal the second (column 1), and for the probability that the first parameter is strictly larger than the second conditional on gender (columns 2 and 3). Due to space considerations, this table as well as Table 5 do not state results for the probability that the first parameter is strictly smaller than the second. However, if the estimated identified set or 95% confidence interval on the first parameter being strictly larger than the second is $[a, b]$, then the corresponding estimated identified set or 95% confidence interval on the first parameter being strictly smaller than the second is $[1 - b, 1 - a]$.

We begin our analysis by noting that the CI for the probability that past and future subjective probabilities are not equal implies that at least 62% of individuals differ in their past versus future beliefs, thus rejecting a key implicit assumption of NV's analysis (see Subsection 4.3). Turning our attention to the second and third columns of results, the CIs imply that at least 54% (and perhaps as high as 86%) of women are overly pessimistic about their chances of winning a past tournament.[30] The corresponding CIs for men are relatively uninformative, as we are unable to reject that as many as 75% or as few as 33% of men are overly pessimistic about past tournaments. For future tournaments, we find that at least 49% (and possibly as high as 81%) of men are overly optimistic about their chances of winning a future tournament. The corresponding results for women are relatively uninformative, as we are unable to reject that as many as 59% or as few as 28% of women are overly optimistic about future tournaments. Finally, we find that the majority of men have higher subjective probabilities of winning a future than a past tournament, while we cannot reject the null hypothesis that half of women have higher and half lower subjective probabilities of winning a future versus past tournament. In summary, we find that most women are overly pessimistic about their chances of winning a past tournament, that a substantial fraction (though not necessarily a majority) of men are optimistic about their chances of winning a future tournament, and that the majority of men are more confident in their chances of winning a future than a past tournament, with the data being relatively uninformative about the remaining comparisons.

This table also highlights the heterogeneity across individuals, including within gender. For example,

[30] To highlight how we obtain these values, observe that the CI for $P[X > Y]$ for women is $(0.14, 0.46)$. As discussed above, this implies that the CI for $P[X < Y]$–which indicates pessimism about changes of winning–is $(1-0.46, 1-0.14) = (0.54, 0.86)$.

Table 4: Relative beliefs

No.	Variable X	Variable Y	All $P[X \neq Y] \in$	Male $P[X > Y] \in$	Female
(1)	Past subjective probability	Objective probability	[0.86,1.00] (0.81,1.00)	[0.39,0.53] (0.25,0.67)	[0.22,0.36] (0.14,0.46)
(2)	Future subjective probability	Objective probability	[0.91,1.00] (0.87,1.00)	[0.64,0.67] (0.49,0.81)	[0.37,0.49] (0.28,0.59)
(3)	Future subjective probability	Past subjective probability	[0.70,1.00] (0.62,1.00)	[0.72,0.92] (0.60,0.99)	[0.49,0.84] (0.39,0.91)

Notes: This table presents mean estimated identified sets (in brackets) and 95% CIs (in parentheses) for the indicator that $X \neq Y$ for all and for the indicator that $X > Y$ by gender. For all results, if the identified set or 95% CI for $P[X > Y]$ is $[a, b]$, the the identified set or 95% CI for $P[X < Y]$ is $[1 - b, 1 - a]$. Notation follows that of Subsection 6.3 and identified sets for parameters are explicitly defined in Online Appendix Table G.2. Sample is restricted to those individuals in the model sample with bounded identified sets for all parameters considered in this section.

the CIs imply that at least 54% of women are overly pessimistic and at least 14% of women are overly optimistic about their chances of winning a past tournament. Thus, while we find that women on average are overly pessimistic about their chances of winning a past tournament, and that the majority of women are overly pessimistic about those chances, there is still a substantial fraction of women who are overly optimistic about those chances.

6.3.2 Analysis by gender and performance level

Table 5 replicates Table 4 but conditional on gender and performance level, where high/low performance was defined in Subsection 6.2.2. We find that the vast majority (at least 87%, as high as 100%) of low performing men are overly optimistic about their chances of winning future tournaments, while a substantial fraction (though possibly less than half) are overly optimistic about past tournaments. In contrast, the vast majority of both high performing men and high performing women are overly pessimistic about their chances of winning a past or future tournament. The corresponding CIs for low performing women are less informative, as we are unable to reject that a sizeable majority are pessimistic or that a sizeable majority are optimistic about their chances of winning a future or past tournament. The majority of low and high performing men are more confident that they will win a future tournament than a past tournament. We find that at least nearly half of high performing women are more confident that they will win a future than a past tournament, while the corresponding results for low performing women are

Table 5: Relative beliefs, by performance

			Low Performance		High Performance	
			Male	Female	Male	Female
No.	Variable X	Variable Y	$P[X > Y] \in$			
(1)	Past subjective probability	Objective probability	[0.59,0.82]	[0.34,0.52]	[0.07,0.07]	[0.00,0.04]
			(0.41,0.96)	(0.22,0.65)	(-0.07,0.21)	(0.00,0.12)
(2)	Future subjective probability	Objective probability	[0.95,0.95]	[0.48,0.66]	[0.14,0.21]	[0.17,0.17]
			(0.87,1.00)	(0.35,0.78)	(-0.03,0.41)	(0.02,0.33)
(3)	Future subjective probability	Past subjective probability	[0.73,0.91]	[0.41,0.82]	[0.71,0.93]	[0.65,0.87]
			(0.57,1.00)	(0.29,0.91)	(0.51,1.00)	(0.49,0.99)

Notes: This table presents mean estimated identified sets (in brackets) and 95% CIs (in parentheses) for the indicator that $X > Y$ by gender and performance status. An individual is high performance if their objective probability of winning is greater than or equal to 25%, and is otherwise low performance. For all results, if the identified set or 95% CI for $P[X > Y]$ is $[a, b]$, the the identified set or 95% CI for $P[X < Y]$ is $[1-b, 1-a]$. Notation follows that of Subsection 6.3 and identified sets for parameters are explicitly defined in Online Appendix Table G.2. Sample is restricted to those individuals in the model sample with bounded identified sets for all parameters considered in this section.

relatively uninformative.

Thus, the finding from Table 4 that a substantial fraction of men are overconfident in their chances of winning a future tournament is driven by low performing men, while the result that the majority of women are overly pessimistic about their chances of winning a past tournament appears to be driven by high performing women. The majority of low and high performing men are more confident in their chances of winning a future as opposed to past tournament, with us being unable to reject that half of both low performing and high performing women are more (or less) optimistic about future as opposed to past performance.

Finally, while we find less evidence of heterogeneity when conditioning on gender and performance level than we did in Table 4 when conditioning only on gender, we continue to find considerable heterogeneity in beliefs for low performing women: we find, for instance, that at least 22% of low performing women are overly optimistic while at least 35% of low performing women are overly pessimistic about their chances of winning a past tournament.

7 Conclusion

Researchers that employ laboratory experiments to study self-selection into compensation schemes often use individuals' revealed choices to make conclusions about their latent preferences and beliefs. However, researchers often do not explicitly model how choices relate to latent factors, leaving open the possibility that conclusions about beliefs and preferences hinge on implicit assumptions. Our analysis begins by formally analyzing the seminal design of Niederle and Vesterlund (2007). Building on their insights, we formulate a simple economic model of self-selection into compensation schemes based on their hypothesized determinants of self-selection.

We use our economic model and individuals' revealed choices to (partially) identify the determinants of self-selection into alternative compensation schemes in a laboratory setting. Our methodology emphasizes that identification depends jointly on assumptions about how individuals self-select into compensation schemes and on the choice of experimental design, and allows us to formally evaluate the threats to identification raised by Niederle and Vesterlund (2007) in interpreting their own conclusions. We show that, for a large class of belief and preference parameters, the sharp identified sets can be constructed by a pair of linear programs. We develop necessary and sufficient conditions for the identified sets to be bounded and/or informative, with resulting implications for experimental design. We aggregate the individual-level parameters and implement the confidence intervals proposed in Imbens and Manski (2004) for inference on the aggregate parameters, justifying the use of such confidence intervals in our context by adapting the results of Stoye (2009) and the analysis of Bhattacharya, Shaikh, and Vytlacil (2012).

Our empirical application illustrates our framework while contributing to the experimental gender and competition literature. Our analysis of gender differences in the value of compensation schemes extends and is consistent with the existing literature. However, we reject key assumptions implicitly required for studies using the NV design to conclude that their results imply a gender difference in preferences for entering a future tournament. In particular, our empirical analysis rejects that individuals have the same beliefs for their chances of winning future versus past tournaments, and further rejects that men and women have the same mean beliefs conditional on past performance and rank guess.

Without imposing such assumptions, we find evidence that men are substantially more confident than women and more confident than objective measures in their chances of winning a future (but not necessarily a past) tournament. These results are largely driven by low performing men tending to be vastly overconfident in their chances of winning a future tournament, with us finding, for instance, that at least 87% of low performing men are overly confident that they will win a future tournament compared to their objective chances and they have on average at least a seven percentage point higher subjective probability of winning a future tournament than comparable women. We find that women, and especially high performing women, enjoy competing in tournaments, while we find no such evidence for men. Our results thus suggest that what has commonly been attributed to a gender difference in non-monetary preferences is instead explained by men, and especially low ability men, having far greater confidence in their probability of winning a future tournament compared to women.

Our findings relate to the recent literature which suggests that the observed gender gap reflects gender differences in beliefs and confidence rather than preference for competition (van Veldhuizen, 2022). We contribute to the literature in part by using revealed choices to study how beliefs of future success diverge from beliefs of past success and how those beliefs relate to both gender and performance level. Our findings also relate to the literature on decision-making under risk and uncertainty. It is commonly observed that individuals assign different probability judgments for the same event depending on whether the certainty is resolved but not revealed before their choice or whether the certainty is resolved after their choice (Rothbart and Snyder, 1970; Tannenbaum, Fox, and Ülkümen, 2017). Although the probability of winning may change across past and future tournaments and is thus not constant, our findings similarly point to a setting in which beliefs about past and future events differ.

Our results can also be linked to the literature on gender differences in belief formation and belief updating (Barber and Odean, 2001; Bordalo, Coffman, Gennaioli, and Shleifer, 2019; Shastry, Shurchkov, and Xia, 2020). Perhaps our most striking empirical finding is that low performing men, but not low performing women, are vastly more confident of future success than of past success or of objective measures of likelihood of future success. In line with this literature, we conjecture that low performing men may attribute their poor past performances to mere bad luck and remain optimistic about winning competitions based on future performances.

Failing to account for the possibility that future and past beliefs differ may lead to erroneous conclusions in literatures beyond that of gender and competition. For example, the entrepreneurship literature documents that entrepreneurs do not change occupations despite repeated failures and lower earnings relative to employees. Although some studies interpret this fact as evidence that these individuals have a taste for being an entrepreneur (e.g. Hamilton (2000)), this fact can be equivalently interpreted as entrepreneurs being consistently optimistic about future success despite past failure. In many settings, researchers have a certain degree of flexibility in choosing what data to collect. Our methodology emphasizes the importance of making explicit how observed data relates to latent parameters of interest, and further highlights how doing so prior to collecting data may guide the design of experiments, and, more generally, the data-collection process.

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A Examples of Corollary 3.1

Corollary 3.1 provides a general approach for constructing $\mathcal{S}_f$-sharp identified sets on functions of parameters across distinct schemes. We develop three examples of Corollary 3.1 that we use in our application. We use Example A.1 to construct bounds on the difference in perceived probabilities of winning past and future tournaments, we use Example A.2 to construct bounds on measures of overconfidence defined as indicators for perceived probabilities of winning exceeding the objective probabilities, and we use Example A.3 to construct bounds on averages of target parameters across multiple past tournament schemes. This last example requires slightly modifying our set of compensation schemes $\mathcal{J}$, which, for ease of notation, included a single past piece-rate scheme and a single past tournament scheme. In our application, we elicit choices for n past tournament and n past piece-rate schemes, where $n = 3$. The analysis of Sections 3 and 4 immediately extends to this setting by instead defining $\mathcal{J} = \{f, \mathcal{J}_n^p, \mathcal{J}^f\}$, where $\mathcal{J}^f$ is as in Definition 1 and

$$\mathcal{J}_n^p = \left\{ \{(pr,k)\}_{k=1,\dots,n}, \{(pt,k)\}_{k=1,\dots,n} \right\} \qquad (\textit{past schemes}).$$

Example A.1. Consider any $j, j' \in \mathcal{J} \setminus \{f, pr\}$, $j \neq j'$, and any τ_{ij} and $\tau_{ij'}$ respectively corresponding to components of $(\beta(\theta_{ij}), \lambda(\theta_{ij}))$ and $(\beta(\theta_{ij'}), \lambda(\theta_{ij'}))$. Applying Corollary 3.1 with g given by $g(x, y) = x - y$, we have that the $\mathcal{S}_f$-sharp identified set for $\tau_{ij} - \tau_{ij'}$ is $[\tau_{ij,l} - \tau_{ij',u} \ , \ \tau_{ij,u} - \tau_{ij',l}]$. The identified set is bounded (respectively, informative) if the $\mathcal{S}_f$-sharp identified sets for τ_{ij} and $\tau_{ij'}$ are bounded (respectively, informative).

Example A.2. Consider any $j, j' \in \mathcal{J} \setminus \{f, pr\}$, $j \neq j'$, and any τ_{ij} and $\tau_{ij'}$ respectively corresponding to components of $(\beta(\theta_{ij}), \lambda(\theta_{ij}))$ and $(\beta(\theta_{ij'}), \lambda(\theta_{ij'}))$. Applying Corollary 3.1 with g given by $g(x, y) = \mathbb{1}\{x - y \in A\}$ for some set $A \subset \mathbb{R}$, we have that the $\mathcal{S}_f$-sharp identified set for $\mathbb{1}\{\tau_{ij} - \tau_{ij'} \in A\}$ is $\{1\}$ if the $\mathcal{S}_f$-sharp identified set for $\tau_{ij} - \tau_{ij'}$ is a subset of A, is $\{0\}$ if this set is a subset of the complement of A, and is $\{0, 1\}$ otherwise. A necessary condition for the identified set to be informative is that the $\mathcal{S}_f$-sharp identified sets for τ_{ij} and $\tau_{ij'}$ are informative.

Example A.3. Index the n past tournament schemes as (pt, k) for $k = 1, \dots, n$. Consider either $\tau_{i,(pt,k)} = \delta_{i,(pt,k)}$ for all k, $\tau_{i,(pt,k)} = \pi_{i,(pt,k)}$ for all k, or $\tau_{i,(pt,k)} = \gamma_{i,(pt,k)}$ for all k. Define $\mathcal{L}_i$ as the set of indices k such that the $\mathcal{S}_f$-sharp identified set for $\tau_{i,(pt,k)}$ is bounded. Suppose this set is non-empty, so that $L \equiv |\mathcal{L}_i| > 0$. With slight abuse of notation, relabel the indices in $\mathcal{L}_i$ as $\ell = 1, \ldots, L$. Consider applying Corollary 3.1 with g given by $g(x_1, \ldots, x_L) = \frac{1}{L}\sum_{\ell=1}^{L} x_\ell$. Depending on the choice of $\tau_{i,(pt,k)}$, $g(\tau_{ij_1}, \ldots, \tau_{ij_L})$ respectively corresponds to the average subjective expected monetary earnings of a past tournament (denoted $\delta_{i,pt}$), the average subjective probability of winning a past tournament (denoted $\pi_{i,pt}$), or the average expected value of feedback aversion for past tournaments (denoted as $\gamma_{i,pt}$, or, equivalently, as $\psi_{i,pt}$), where averages are taken over schemes for which identified sets are bounded. Then the corollary states that the $\mathcal{S}_f$-sharp identified set is $\left[\frac{1}{L}\sum_{\ell=1}^{L} \tau_{i,(pt,k),l} \ , \ \frac{1}{L}\sum_{\ell=1}^{L} \tau_{i,(pt,k),u}\right]$. If $\tau_{i,(pt,k)}$ is bounded for at least some $k = 1, \ldots, n$, then the identified set is bounded.

B Inference

We apply the confidence intervals proposed by Imbens and Manski (2004) for inference on aggregated (cross-individual) partially identified parameters. We first summarize their proposed confidence interval. Suppose one has a sample of random variables from some distribution $P \in \mathbf{P}$. Let $\mu_0(P)$ denote an interval-identified parameter of interest that lies in the set $[\mu_l(P), \ \mu_u(P)]$. Suppose that $(\hat{\mu}_{l,n}, \hat{\mu}_{u,n})$ is an asymptotically normal estimator of (μ_l, μ_u), with corresponding standard errors $\hat{\sigma}_{l,n}, \hat{\sigma}_{u,n}$. Imbens and Manski (2004) propose the following confidence interval:

$$\mathrm{CI}_\alpha = \left[\hat{\mu}_{l,n} - \frac{C_\alpha \hat{\sigma}_{l,n}}{\sqrt{n}}, \ \hat{\mu}_{u,n} + \frac{C_\alpha \hat{\sigma}_{u,n}}{\sqrt{n}}\right], \tag{B.1}$$

where C_α is defined as the value that solves

$$\Phi\left(C_\alpha + \frac{\sqrt{n}\hat{\Delta}_n}{\max\{\hat{\sigma}_{l,n}, \hat{\sigma}_{u,n}\}}\right) - \Phi(-C_\alpha) = 1 - \alpha, \tag{B.2}$$

with $\hat{\Delta}_n \equiv \hat{\mu}_{u,n} - \hat{\mu}_{l,n}$. Imbens and Manski (2004) establish conditions on $\mathbf{P}$ such that the confidence interval of (B.1) is uniformly consistent in level over $\mathbf{P}$:

$$\lim_{n\to\infty} \inf_{P\in\mathbf{P}} \inf_{\mu_0 \in [\mu_l(P), \ \mu_u(P)]} P[\mu \in \mathrm{CI}_\alpha] = 1 - \alpha. \tag{B.3}$$

Stoye (2009) establishes weaker conditions on $\mathbf{P}$ for equation (B.3) to hold.

Consider the following special case of the above framework. Let (Y_i, Z_i, G_i), $i = 1, \ldots, n$ be an i.i.d. sequence of random variables with distribution $P \in \mathbf{P}$. For any random variable U, let $\mu_{U|G=g}(P) \equiv E_P[U \mid G = g]$, $\sigma^2_{U|G=g}(P) = E_P[(U - \mu_{U|G=g}(P))^2 \mid G = g]$, $\bar{U}_g \equiv \frac{1}{n_g}\sum_{i:G_i=g} U_i$ and $\hat{\sigma}^2_{U|G=g} \equiv \frac{1}{n_g}\sum_{i:G_i=g}(U_i - \bar{U}_g)^2$, where $n_g = \sum_i \mathbb{1}\{G_i = g\}$. For some groups g_0, g_1 and $(a_0, a_1) \in \{(1,0), (1,-1)\}$, suppose

$$\mu_l(P) = a_0 \cdot \mu_{Y|G=g_0}(P) + a_1 \cdot \mu_{Z|G=g_1}(P), \tag{B.4}$$

$$\mu_u(P) = a_0 \cdot \mu_{Z|G=g_0}(P) + a_1 \cdot \mu_{Y|G=g_1}(P), \tag{B.5}$$

with sample analogs

$$\hat{\mu}_{l,n} \equiv a_0 \cdot \bar{Y}_{g_0} + a_1 \cdot \bar{Z}_{g_1}, \tag{B.6}$$

$$\hat{\mu}_{u,n} \equiv a_0 \cdot \bar{Z}_{g_0} + a_1 \cdot \bar{Y}_{g_1}, \tag{B.7}$$

and corresponding standard errors as the square-roots of

$$\hat{\sigma}^2_{l,n} \equiv a_0^2 \, \frac{\hat{\sigma}^2_{Y|G=g_0}}{n_0} + a_1^2 \, \frac{\hat{\sigma}^2_{Z|G=g_1}}{n_1}, \tag{B.8}$$

$$\hat{\sigma}^2_{u,n} \equiv a_0^2 \, \frac{\hat{\sigma}^2_{Z|G=g_0}}{n_0} + a_1^2 \, \frac{\hat{\sigma}^2_{Y|G=g_1}}{n_1}. \tag{B.9}$$

In our application, we use examples with $(a_0, a_1) = (1, 0)$ to construct confidence intervals on target parameters by gender, and we use examples with $(a_0, a_1) = (1, -1)$ to construct confidence intervals on mean differences in target parameters across genders. Consider the following assumption:

Assumption 2. Let (Y_i, Z_i, G_i), $i = 1, ..., n$ be an i.i.d. sequence of random variables with distribution $P \in \mathbf{P}$. Assume that

1. $P[Y_i \leq Z_i] = 1 \;\; \forall \; P \in \mathbf{P}$;
2. There exists finite sets $\mathcal{Y}$, $\mathcal{Z}$, $\mathcal{G}$ such that
   (a) $P[(Y_i, Z_i, G_i) \in \mathcal{Y} \times \mathcal{Z} \times \mathcal{G}] = 1 \;\; \forall \; P \in \mathbf{P}$;
   (b) For some $\epsilon > 0$,
      i. $\inf_{P \in \mathbf{P}} P[G_i = g] > \epsilon$,
      ii. $\sup_{P \in \mathbf{P}} P[Y_i = y \mid G_i = g] < 1 - \epsilon$,
      iii. $\sup_{P \in \mathbf{P}} P[Z_i = z \mid G_i = g] < 1 - \epsilon$,

   for all $(y, z, g) \in \mathcal{Y} \times \mathcal{Z} \times \mathcal{G}$.

Note that $(a_0, a_1) \in \{(1, 0), (1, -1)\}$ and Assumption 2.1 imply that $P[\hat{\mu}_{u,n} \geq \hat{\mu}_{l,n}] = 1$ for all $P \in \mathbf{P}$. Assumption 2.2 implies that $|Y_i|, |Z_i|$ are uniformly bounded from above, and that the variances of Y_i and Z_i are bounded from below and above. Assumption 2.2 also includes that $P[G_i = g]$ is bounded from below, which will be critical to obtain uniform results for means conditional on $G_i = g$.

We now have the following theorem.

Theorem B.1. *Let Assumption 2 hold. Suppose that for some $g_0, g_1 \in \mathcal{G}$ and $(a_0, a_1) \in \{(1, 0), (1, -1)\}$, $\mu_0(P) \in [\mu_l(P),\ \mu_u(P)]$ with $\mu_l(P)$ and $\mu_u(P)$ given by* (B.4)-(B.5). *Let $\hat{\mu}_{l,n}, \hat{\mu}_{u,n}, \hat{\sigma}^2_{l,n}$, and $\hat{\sigma}^2_{u,n}$ be given by equations* (B.6)-(B.9). *Then:*

1. *$\hat{\mu}_l$, $\hat{\mu}_u$ converge to $\mu_l(P), \mu_u(P)$ uniformly in $P \in \mathbf{P}$;*
2. *CI_α defined by equation* (B.1) *satisfies* (B.3).

The proof of Result 1. of Theorem B.1 follows from modifying the arguments used in Lemmas (B.1)-(B.3) of Bhattacharya, Shaikh, and Vytlacil (2012). By Lemma 3. and Proposition 1. of Stoye (2009), Result 2. of Theorem B.1 can be proven by verifying his assumptions Assumptions 1(i), 1(ii) and 3. His Assumption 3. is that $P[\hat{\mu}_{u,n} \geq \hat{\mu}_{l,n}] = 1$ for all $P \in \mathbf{P}$, which follows immediately from our Assumption 2.1. His Assumption 1(i) follows from our Assumption 2.2, as is straightforward to verify by modifying the arguments used in Lemmas (B.1)-(B.5) of Bhattacharya, Shaikh, and Vytlacil (2012). His Assumption 1(ii) also follows from our Assumption 2.2, as is straightforward to verify by modifying the arguments used in Lemmas (B.1)-(B.3) of Bhattacharya, Shaikh, and Vytlacil (2012).

We now consider applying Theorem B.1 in our context. In the following examples, we take $(D_{i,\mathcal{V}}, X_i)$, $i = 1, ..., n$ to be an i.i.d. sequence with distribution $P \in \mathbf{P}$. For notational ease, we define $\bar{\beta}(\theta_i) \equiv \{\beta(\theta_{ij})\}_{j\in\mathcal{J}}$, $\bar{\lambda}(\theta_i) \equiv \{\lambda(\theta_{ij})\}_{j\in\mathcal{J}}$, and $\bar{\lambda}_1(\theta_i) \equiv \{\lambda_1(\theta_{ij})\}_{j\in\mathcal{J}}$.

Example B.1 (Payoff Indifference Points)**.** Following Definition 7, suppose that the indifference point for (j, j', p) is uniquely defined w.p.1. and let q_i^* denote that indifference point so that $q_i^* \in [q_{l,(j,j')}(p;i), q_{u,(j,j')}(p;i)]$. Recall that $\mathcal{V}$ is assumed to be finite. Suppose that $q_{l,(j,j')}(p;i), q_{u,(j,j')}(p;i)$ are finite w.p.1, so that $q_{l,(j,j')}(p;i)$ and $q_{u,(j,j')}(p;i)$ must be equal to one of the finitely many q in $\mathcal{V}$ by definition. For some $(a_0, a_1) \in \{(1,0),(1,-1)\}$ and $g_0, g_1 \in \mathcal{G}$, taking $\mu_0 = a_0 E[q_i^* \mid G_i = g_0] + a_1 E[q_i^* \mid G_i = g_1]$ and $(Y_i,\ Z_i) = (q_{l,(j,j')}(p;i),\ q_{u,(j,j')}(p;i))$, we have that Assumption 2.1 and 2.2(a) are satisfied. Imposing Assumption 2.2(b), by Theorem B.1 the confidence interval of CI_α defined by equation (B.1) is uniformly consistent in level for μ_0. Note that in this example we require the relevant payoff indifference set to be bounded, but the $\mathcal{S}_f$-sharp identified set on components of $\bar{\beta}(\theta_i)$, $\bar{\lambda}(\theta_i)$ need not be bounded.

Example B.2 (Components of $\bar{\beta}(\theta_i)$ and $\bar{\lambda}_1(\theta_i)$)**.** Let $\tau_i^\star$ denote a component of $\bar{\beta}(\theta_i)$, of $\bar{\lambda}_1(\theta_i)$, or a cross-scheme difference in such components as in Example A.1. In all of these cases, if it is bounded, the $\mathcal{S}_f$-sharp identified set has the form of an identified interval $[\tau_{i,l}, \tau_{i,u}]$. Recall that $\mathcal{V}$ is a finite set. Suppose that there exists $\bar{S}$ such that $S_{ij}^* \le \bar{S}$ w.p.1 for all $j \in \mathcal{J}_n^p$, $P \in \mathbf{P}$, and further that $\tau_{i,l}, \tau_{i,u}$ are finite w.p.1 for all $P \in \mathbf{P}$. Then $\tau_{i,l}, \tau_{i,u}$ are necessarily functions of $(D_{i,\mathcal{V}}, X_{1i})$, where $(D_{i,\mathcal{V}}, X_{1i})$ is a discrete random vector that takes a finite number of potential values so that $\tau_{i,l}, \tau_{i,u}$ can take at most a finite number of values. For some $(a_0, a_1) \in \{(1,0),(1,-1)\}$ and $g_0, g_1 \in \mathcal{G}$, taking $\mu_0 = a_0 E[\tau_i^\star \mid G_i = g_0] + a_1 E[\tau_i^\star \mid G_i = g_1]$ and $(Y_i,\ Z_i) = (\tau_{i,l},\ \tau_{i,u})$, we have that Assumption 2.1 and 2.2(a) are satisfied. Imposing Assumption 2.2(b), by Theorem B.1 the confidence interval of CI_α defined by equation (B.1) is uniformly consistent in level for μ_0. That $\tau_{i,l}, \tau_{i,u}$ are finite w.p.1 for all $P \in \mathbf{P}$ will require that the appropriate elements of $\bar{\beta}(\theta_i)$, $\bar{\lambda}(\theta_i)$ are bounded w.p.1 for all $P \in \mathbf{P}$.

Example B.3 (Indicator Target Parameters)**.** Following Example A.2, for some $j, j' \in \mathcal{J} \setminus \{f, pr\}$, $j \neq j'$, τ_{ij} and $\tau_{ij'}$ components of $(\bar{\beta}(\theta_i), \bar{\lambda}(\theta_i))$, and some set $A \subset \mathbb{R}$, let Υ_i denote the $\mathcal{S}_f$-sharp identified set for $\mathbb{1}\{\tau_{ij} - \tau_{ij'} \in A\}$ so that $\Upsilon_i \in \big\{\{0\},\{1\},\{0,1\}\big\}$. For some $(a_0, a_1) \in \{(1,0),(1,-1)\}$, $g_0, g_1 \in \mathcal{G}$, taking $\mu_0 \equiv a_0 P[\tau_{ij} - \tau_{ij'} \in A \mid G_i = g_0] + a_1 P[\tau_{ij} - \tau_{ij'} \in A \mid G_i = g_1]$, $(Y_i,\ Z_i) = (\mathbb{1}\big\{\Upsilon_i = \{1\}\big\},\ \mathbb{1}\big\{\Upsilon_i \in \{\{1\},\{0,1\}\}\big\})$, we have that $\mu_0(P) \in [\mu_l(P),\ \mu_u(P)]$ and that Assumption 2.1 and 2.2(a) are satisfied. Imposing Assumption 2.2(b), by Theorem B.1 the confidence interval of CI_α defined by equation (B.1) is uniformly consistent in level for μ_0. Note that in this example the payoff indifference sets and the $\mathcal{S}_f$-sharp identified sets on components of $\bar{\beta}(\theta_i)$, $\bar{\lambda}(\theta_i)$ need not be bounded.

Online Appendix for

Eliciting Willingness-to-Pay to Decompose Beliefs and Preferences that Determine Selection into Competition in Lab Experiments

Appendix A Additional empirical results

Table A.1: Task performances (baseline sample)

	Average performance		
	Male	Female	Male - Female
Combined			
Practice	7.23	6.13	1.10**
	(0.29)	(0.17)	(0.44)
Main	8.42	7.30	1.12**
	(0.18)	(0.11)	(0.48)
Piece Rate			
Base-payoff: 0.8	8.06	7.04	1.03**
	(0.43)	(0.29)	(0.51)
Base-payoff: 1.6	8.57	7.23	1.35***
	(0.42)	(0.23)	(0.48)
Base-payoff: 2.4	8.43	7.39	1.04*
	(0.48)	(0.27)	(0.55)
Tournament			
Base-payoff: 3.2	8.06	6.94	1.12**
	(0.46)	(0.27)	(0.53)
Base-payoff: 6.4	8.65	7.70	0.95*
	(0.45)	(0.25)	(0.51)
Base-payoff: 9.6	8.75	7.50	1.25**
	(0.47)	(0.28)	(0.55)

Notes: *p<0.1; **p<0.05; ***p<0.01. This table presents average task performance by gender, compensation scheme (all tasks combined, piece rate, or tournament), and base-payoff. Gender differences for each scheme-payoff are presented in the third column. Standard errors are reported in parentheses. Standard errors for combined estimates are clustered at the individual level. Hypothesis testing was only conducted on gender differences. Sample is restricted to the baseline sample. Practice tasks are unpaid and performed before the main experiment.

Table A.2: MPL behavior (baseline sample)

MPL type	Gender	Bounded	Unbounded below	Unbounded above
Past Tournament - Fixed Pay (avg)	male	0.91	0.00	0.09
Past Tournament - Fixed Pay (avg)	female	0.99	0.01	0.00
Future Tournament - Fixed Pay	male	0.88	0.00	0.12
Future Tournament - Fixed Pay	female	0.98	0.02	0.00
Future Piece Rate - Fixed Pay	male	0.99	0.00	0.00
Future Piece Rate - Fixed Pay	female	0.98	0.01	0.00
Future Lumpsum Tournament - Fixed Pay	male	0.92	0.00	0.08
Future Lumpsum Tournament - Fixed Pay	female	0.98	0.02	0.00
Future Tournament - Future Piece Rate	male	0.97	0.01	0.02
Future Tournament - Future Piece Rate	female	0.98	0.02	0.00

Notes: This table presents shares of MPLs that result in payoff indifference sets that are bounded, unbounded below, and unbounded above by gender and MPL type. MPLs take the form of 'scheme X – scheme Y', where scheme X is fixed at the listed base-payoff and scheme Y varies in base-payoff. MPLs with '(avg)' denote taking, for each individual, the mean of multiple MPLs at the given base-payoff, as is the case for past tournament since individuals perform three past tasks and complete MPLs at the listed base-payoffs for each of these past performances. Sample is restricted to the baseline sample. Shares for each gender and MPL type may not sum to 1 due to rounding.

Table A.3: Mean payoff indifference sets, by gender (baseline sample with bounded sets)

MPL type	Base-payoff	Male	Female	Male - Female
Past Tournament - Fixed Pay (avg)	3.2	[6.25,6.84]	[4.50,5.02]	[1.23,2.34]
		(5.22,7.94)	(3.72,5.83)	(-0.06,3.66)
Past Tournament - Fixed Pay (avg)	6.4	[10.91,12.04]	[7.42,8.39]	[2.51,4.62]
		(9.04,14.02)	(6.07,9.80)	(0.21,6.98)
Past Tournament - Fixed Pay (avg)	9.6	[16.38,18.25]	[10.68,12.24]	[4.13,7.56]
		(13.26,21.61)	(8.67,14.38)	(0.42,11.41)
Future Tournament - Fixed Pay	3.2	[6.49,7.13]	[4.63,5.14]	[1.36,2.50]
		(5.34,8.36)	(3.88,5.92)	(-0.01,3.91)
Future Tournament - Fixed Pay	6.4	[11.76,12.97]	[6.93,7.87]	[3.88,6.04]
		(9.42,15.47)	(5.71,9.12)	(1.29,8.76)
Future Tournament - Fixed Pay	9.6	[16.52,18.11]	[9.22,10.60]	[5.92,8.89]
		(13.14,21.69)	(7.48,12.39)	(2.19,12.78)
Future Lumpsum Tournament - Fixed Pay	6.4	[2.44,2.60]	[2.19,2.37]	[0.08,0.41]
		(2.15,2.90)	(1.91,2.66)	(-0.33,0.81)
Future Lumpsum Tournament - Fixed Pay	12.8	[4.77,5.11]	[3.66,3.98]	[0.79,1.45]
		(4.22,5.69)	(3.20,4.44)	(0.09,2.18)
Future Lumpsum Tournament - Fixed Pay	19.2	[7.43,7.95]	[5.01,5.50]	[1.94,2.94]
		(6.64,8.79)	(4.35,6.17)	(0.90,3.99)
Future Piece Rate - Fixed Pay	0.8	[6.40,6.85]	[5.13,5.60]	[0.80,1.73]
		(5.76,7.51)	(4.63,6.10)	(0.00,2.54)
Future Piece Rate - Fixed Pay	1.6	[11.68,12.62]	[10.15,11.10]	[0.58,2.47]
		(10.47,13.87)	(9.29,11.98)	(-0.90,3.98)
Future Piece Rate - Fixed Pay	2.4	[18.58,20.01]	[14.62,15.90]	[2.68,5.40]
		(16.75,21.92)	(13.47,17.06)	(0.53,7.60)
Past Tournament - Past Piece Rate (avg)	3.2	[0.79,0.87]	[0.57,0.64]	[0.15,0.30]
		(0.67,1.00)	(0.48,0.73)	(0.00,0.46)
Past Tournament - Past Piece Rate (avg)	6.4	[1.34,1.50]	[0.92,1.07]	[0.27,0.57]
		(1.14,1.71)	(0.78,1.22)	(0.03,0.83)
Past Tournament - Past Piece Rate (avg)	9.6	[1.97,2.22]	[1.34,1.57]	[0.40,0.88]
		(1.64,2.57)	(1.11,1.81)	(-0.00,1.29)
Future Tournament - Future Piece Rate	3.2	[1.42,1.56]	[1.00,1.10]	[0.32,0.57]
		(1.23,1.77)	(0.86,1.24)	(0.09,0.81)
Future Tournament - Future Piece Rate	6.4	[2.76,3.05]	[1.60,1.81]	[0.95,1.45]
		(2.37,3.48)	(1.37,2.05)	(0.49,1.93)
Future Tournament - Future Piece Rate	9.6	[3.58,3.99]	[2.29,2.63]	[0.95,1.70]
		(3.06,4.57)	(1.90,3.06)	(0.28,2.39)

Notes: This table presents bounds (in brackets) and 95% CIs (in parentheses) for mean payoff indifference sets by gender, MPL type, and base-payoff. MPLs take the form of ‘scheme X – scheme Y’, where scheme X is fixed at the listed base-payoff and scheme Y varies in base-payoff. MPLs with ‘(avg)’ denote taking, for each individual, the mean of multiple MPLs at the given base-payoff, as is the case for past tournament since individuals perform three past tasks and complete MPLs at the listed base-payoffs for each of these past performances. Sample is restricted to the baseline sample, and we further restrict to bounded payoff indifference sets.

Table A.4: Task performances (model sample)

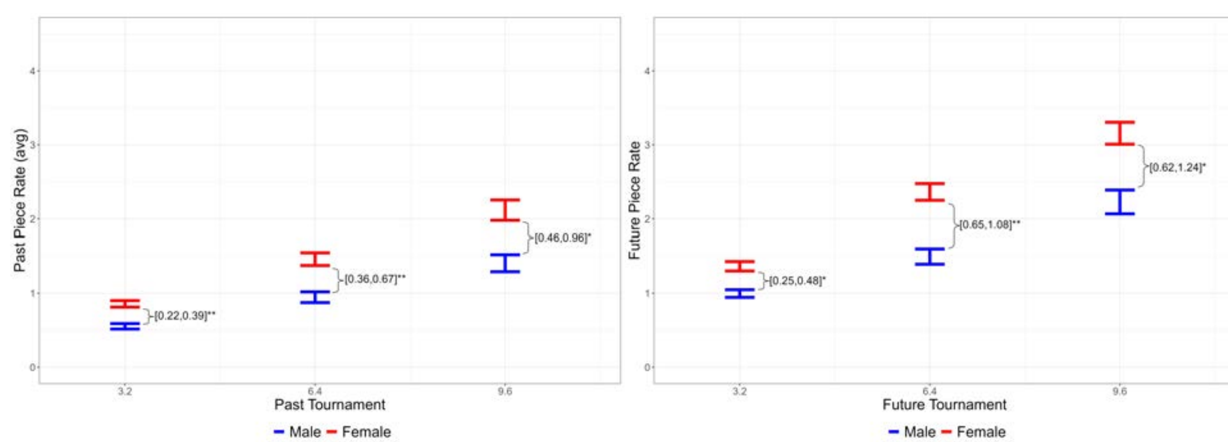
	Average Performance		
	Male	Female	Male-Female
Combined			
Practice	7.60	5.92	1.68***
	(0.37)	(0.19)	(0.54)
Main	8.61	7.15	1.46**
	(0.23)	(0.11)	(0.58)
Piece Rate			
Base payoff: 0.8	8.28	6.91	1.37**
	(0.54)	(0.29)	(0.61)
Base payoff: 1.6	8.89	7.04	1.85***
	(0.54)	(0.24)	(0.59)
Base payoff: 2.4	8.57	7.24	1.33**
	(0.60)	(0.27)	(0.66)
Tournament			
Base payoff: 3.2	8.15	6.76	1.39**
	(0.59)	(0.28)	(0.65)
Base payoff: 6.4	8.72	7.50	1.22*
	(0.57)	(0.25)	(0.63)
Base payoff: 9.6	9.02	7.44	1.58**
	(0.60)	(0.30)	(0.67)

Notes: *p<0.1; **p<0.05; ***p<0.01. This table presents average task performance by gender, compensation scheme (all tasks combined, piece rate, or tournament), and base-payoff. Gender differences for each scheme-payoff are presented in the third column. Standard errors are reported in parentheses. Standard errors for combined estimates are clustered at the individual level. Hypothesis testing was only conducted on gender differences. Sample is restricted to the model sample. Practice tasks are unpaid and performed before the main experiment.

Figure A.1: Tournament payoff indifference sets relative to piece rate (model sample)

(a) Past Tournament vs Past Piece Rate

(b) Future Tournament vs Future Piece Rate



Notes: *p<0.1; **p<0.05; ***p<0.01. Sample mean valuation sets are depicted in blue for men and red for women. Bounds on the difference between mean male and female valuation sets are presented by the curly brackets. For each difference, we test the null of the bounds containing zero. Sample is restricted to the model sample, and we further restrict to bounded payoff indifference sets.

Table A.5: Mean payoff indifference sets, by gender (model sample with bounded sets)

MPL schemes	Price	Male	Female	Male - Female
Past Tournament - Fixed Pay (avg)	3.2	[6.25,6.86]	[4.03,4.53]	[1.72,2.83]
		(4.90,8.30)	(3.19,5.42)	(0.14,4.46)
Past Tournament - Fixed Pay (avg)	6.4	[10.93,12.12]	[6.87,7.83]	[3.10,5.25]
		(8.54,14.67)	(5.38,9.38)	(0.31,8.14)
Past Tournament - Fixed Pay (avg)	9.6	[15.73,17.66]	[10.02,11.55]	[4.19,7.64]
		(11.84,21.87)	(7.79,13.92)	(-0.28,12.30)
Future Tournament - Fixed Pay	3.2	[6.80,7.50]	[4.11,4.60]	[2.20,3.39]
		(5.23,9.19)	(3.35,5.38)	(0.48,5.20)
Future Tournament - Fixed Pay	6.4	[12.29,13.58]	[5.86,6.77]	[5.52,7.72]
		(9.08,17.01)	(4.72,7.91)	(2.21,11.23)
Future Tournament - Fixed Pay	9.6	[16.73,18.45]	[8.27,9.55]	[7.19,10.17]
		(12.12,23.38)	(6.59,11.24)	(2.42,15.23)
Future Lumpsum Tournament - Fixed Pay	6.4	[2.21,2.37]	[2.10,2.27]	[-0.06,0.27]
		(1.81,2.77)	(1.79,2.59)	(-0.56,0.77)
Future Lumpsum Tournament - Fixed Pay	12.8	[4.58,4.92]	[3.26,3.57]	[1.01,1.66]
		(3.89,5.64)	(2.78,4.07)	(0.18,2.50)
Future Lumpsum Tournament - Fixed Pay	19.2	[6.92,7.40]	[4.43,4.91]	[2.01,2.97]
		(5.96,8.41)	(3.74,5.61)	(0.85,4.16)
Future Piece Rate - Fixed Pay	0.8	[5.97,6.41]	[4.92,5.38]	[0.59,1.50]
		(5.19,7.22)	(4.38,5.93)	(-0.35,2.45)
Future Piece Rate - Fixed Pay	1.6	[10.56,11.51]	[9.79,10.72]	[-0.17,1.72]
		(9.06,13.08)	(8.84,11.68)	(-1.92,3.52)
Future Piece Rate - Fixed Pay	2.4	[17.42,18.89]	[14.29,15.58]	[1.84,4.60]
		(15.11,21.33)	(13.05,16.84)	(-0.75,7.29)
Past Tournament - Past Piece Rate (avg)	3.2	[0.81,0.90]	[0.52,0.59]	[0.22,0.39]
		(0.65,1.07)	(0.42,0.69)	(0.03,0.58)
Past Tournament - Past Piece Rate (avg)	6.4	[1.38,1.55]	[0.87,1.02]	[0.36,0.67]
		(1.11,1.82)	(0.70,1.19)	(0.04,0.99)
Past Tournament - Past Piece Rate (avg)	9.6	[1.98,2.25]	[1.29,1.52]	[0.46,0.96]
		(1.55,2.71)	(1.02,1.80)	(-0.05,1.48)
Future Tournament - Future Piece Rate	3.2	[1.30,1.43]	[0.94,1.05]	[0.25,0.48]
		(1.06,1.69)	(0.79,1.20)	(-0.03,0.78)
Future Tournament - Future Piece Rate	6.4	[2.25,2.48]	[1.39,1.60]	[0.65,1.08]
		(1.84,2.90)	(1.15,1.85)	(0.18,1.56)
Future Tournament - Future Piece Rate	9.6	[3.01,3.31]	[2.07,2.39]	[0.62,1.24]
		(2.46,3.87)	(1.67,2.82)	(-0.07,1.92)

Notes: This table presents bounds (in brackets) and 95% CIs (in parentheses) for mean payoff indifference sets by gender, MPL type, and base-payoff. MPLs take the form of 'scheme X – scheme Y', where scheme X is fixed at the listed base-payoff and scheme Y varies in base-payoff. MPLs with '(avg)' denote taking, for each individual, the mean of multiple MPLs at the given base-payoff, as is the case for past tournament since individuals perform three past tasks and complete MPLs at the listed base-payoffs for each of these past performances. Sample is restricted to the model sample, and we further restrict to bounded payoff indifference sets.

Table A.6: Tournament expected monetary earnings (model sample with bounded sets)

No.	Parameter	Description	Male	Female	Male - Female
Panel A: tournament expected monetary earnings					
(1)	$\pi^*\mu^*$	Objective	2.87	2.14	0.73
		tournament expected monetary value	(1.66,4.08)	(1.54,2.75)	(-0.62,2.07)
(2)	$\pi_{pt}\mu_{pt}$	Past subjective	[1.49,1.85]	[0.71,1.03]	[0.46,1.14]
		tournament expected monetary value	(1.05,2.35)	(0.52,1.27)	(-0.04,1.67)
(3)	$\pi_{ft}\mu_{ft}$	Future subjective	[1.58,1.96]	[0.61,0.84]	[0.74,1.36]
		tournament expected monetary value	(1.09,2.54)	(0.45,1.00)	(0.23,1.94)
Panel B: differences in tournament expected monetary earnings					
(4)	$\pi_{pt}\mu_{pt} - \pi^*\mu^*$	Past subjective - objective	[-1.38,-1.02]	[-1.44,-1.11]	[-0.27,0.42]
		tournament expected monetary value	(-2.26,-0.15)	(-1.92,-0.63)	(-1.24,1.38)
(5)	$\pi_{ft}\mu_{ft} - \pi^*\mu^*$	Future subjective - objective	[-1.29,-0.91]	[-1.54,-1.30]	[0.01,0.63]
		tournament expected monetary value	(-2.21,0.03)	(-2.02,-0.83)	(-1.00,1.66)
(6)	$\pi_{ft}\mu_{ft} - \pi_{pt}\mu_{pt}$	Future subjective - past subjective	[-0.27,0.47]	[-0.43,0.13]	[-0.40,0.90]
		tournament expected monetary value	(-0.58,0.84)	(-0.63,0.30)	(-0.75,1.32)

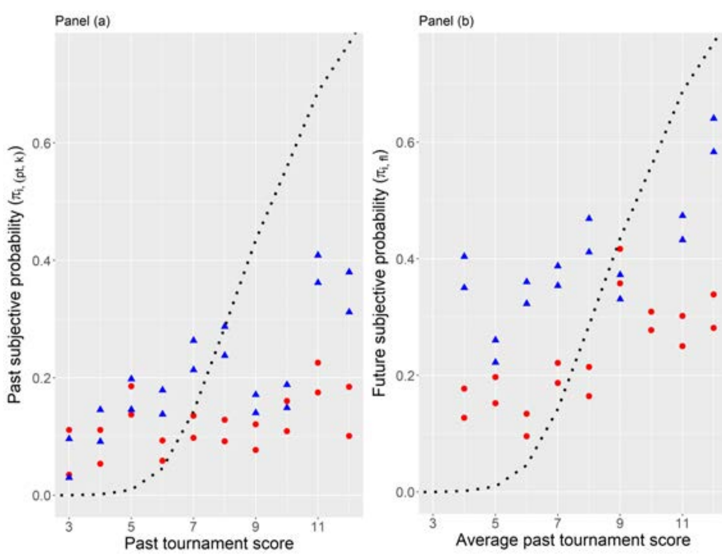
Notes: This table presents mean estimated identified sets (in brackets) and 95% CIs (in parentheses) for belief parameters by gender and for the difference between men and women. Notation and identified sets for parameters are explicitly defined in Online Appendix Table G.1. Sample is restricted to those individuals in the model sample with bounded identified sets for all parameters considered in Section 6.

Table A.7: Tournament expected monetary earnings, by ability (model sample with bounded sets)

No.	Parameter	Description	Low Ability Male	Low Ability Female	Low Ability Male - Female	High Ability Male	High Ability Female	High Ability Male - Female
Panel A: tournament expected monetary earnings								
(1)	$\pi^*\mu^*$	Objective	0.70	0.74	-0.04	6.28	4.84	1.44
		tournament expected monetary value	(0.36,1.04)	(0.55,0.92)	(-0.42,0.35)	(4.19,8.38)	(3.76,5.91)	(-0.85,3.73)
(2)	$\pi_{pt}\mu_{pt}$	Past subjective	[0.94,1.24]	[0.57,0.82]	[0.12,0.67]	[2.36,2.82]	[0.98,1.45]	[0.91,1.84]
		tournament expected monetary value	(0.53,1.72)	(0.37,1.03)	(-0.33,1.19)	(1.53,3.74)	(0.59,1.97)	(-0.05,2.81)
(3)	$\pi_{ft}\mu_{ft}$	Future subjective	[1.12,1.45]	[0.44,0.65]	[0.47,1.01]	[2.31,2.78]	[0.93,1.20]	[1.11,1.84]
		tournament expected monetary value	(0.58,2.10)	(0.28,0.82)	(-0.09,1.67)	(1.41,3.79)	(0.62,1.52)	(0.17,2.88)
Panel B: differences in tournament expected monetary earnings								
(4)	$\pi_{pt}\mu_{pt} - \pi^*\mu^*$	Past subjective - objective	[0.24,0.54]	[-0.17,0.08]	[0.16,0.71]	[-3.92,-3.47]	[-3.86,-3.39]	[-0.54,0.40]
		tournament expected monetary value	(-0.19,1.03)	(-0.40,0.33)	(-0.33,1.24)	(-5.53,-1.91)	(-4.70,-2.51)	(-2.30,2.11)
(5)	$\pi_{ft}\mu_{ft} - \pi^*\mu^*$	Future subjective - objective	[0.42,0.75]	[-0.30,-0.08]	[0.50,1.05]	[-3.97,-3.50]	[-3.91,-3.64]	[-0.34,0.40]
		tournament expected monetary value	(-0.16,1.43)	(-0.48,0.10)	(-0.09,1.74)	(-5.55,-1.93)	(-4.81,-2.75)	(-2.10,2.17)
(6)	$\pi_{ft}\mu_{ft} - \pi_{pt}\mu_{pt}$	Future subjective - past subjective	[-0.12,0.51]	[-0.38,0.09]	[-0.20,0.89]	[-0.51,0.42]	[-0.52,0.23]	[-0.73,0.94]
		tournament expected monetary value	(-0.56,1.03)	(-0.58,0.27)	(-0.68,1.44)	(-0.89,0.91)	(-0.96,0.57)	(-1.25,1.60)

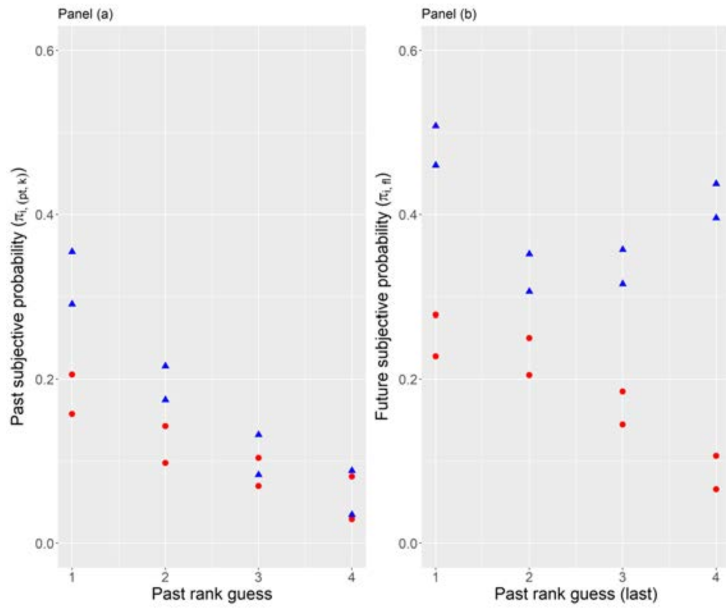
Notes: This table presents mean estimated identified sets (in brackets) and 95% CIs (in parentheses) for belief and preference parameters by gender and for the difference between men and women, by performance status. An individual is high performance if their objective probability of winning is greater than or equal to 25%, and is otherwise low performance. Notation and identified sets for parameters are explicitly defined in Online Appendix Table G.1. Sample is restricted to those individuals in the model sample with bounded identified sets for all parameters considered in Section 6.

Figure A.2: Beliefs by performance (model sample with bounded sets)



Notes: Panel (a) plots estimated bounds on the k-th past tournament subjective probability of winning by gender conditional on past performance, while Panel (b) plots estimated bounds on future subjective probability of winning by gender conditional on average past performance. Blue triangles denote upper and lower estimated mean bounds for men, and red dots denote upper and lower estimated mean bounds for women. The dotted line denotes the objective probability of winning for a given past tournament score. Average past tournament score denotes the average of the three past tournament performances (rounded to closest integer). Notation follows that of Section 3 and Online Appendix G, where $\pi_{i,(pt,k)}$ denotes the past subjective probability of winning the kth past tournament, and $\pi_{i,fl}$ denotes the future subjective probability of winning. Sample is restricted to those individuals in the model sample with bounded identified sets for all parameters considered in Section 6.

Figure A.3: Beliefs by rank guess (model sample with bounded sets)



Notes: Panel (a) plots estimated bounds on the k-th past tournament subjective probability of winning by gender conditional on past rank guess for the associated k-th past tournament, while Panel (b) plots estimated bounds on future subjective probability of winning by gender conditional on the rank guess for last past tournament performance prior to which the individual evaluates choices for future tournament. Blue triangles denote upper and lower estimated mean bounds for men, and red dots denote upper and lower estimated mean bounds for women. Notation follows that of Section 3 and Online Appendix G, where $\pi_{i,(pt,k)}$ denotes the past subjective probability of winning the kth past tournament, and $\pi_{i,fl}$ denotes the future subjective probability of winning. Sample is restricted to those individuals in the model sample with bounded identified sets for all parameters considered in Section 6.

Appendix B Proofs

The following lemma will be useful for proving Theorem 1.

Lemma B.1. *Suppose $\theta \in \tilde{\Theta}_i$. θ satisfies $D_{j,f}(p,q;i) = \mathbb{1}\Big[V_j(p;\theta_j) \geq V_f(q;\theta_f)\Big]$ for all $(j,f,p,q) \in \mathcal{V}$ if and only if $q_{l,(j,f)}(p;i) \leq \delta(\theta_j^{[1]})\ p + \gamma(\theta_j) \leq q_{u,(j,f)}(p;i)$ for all $(j,f) \in \mathcal{S}_f, p \in P_{j,f}$.*

Proof of Lemma B.1. Following Remark 3.2, we can rewrite $D_{j,f}(p,q;i) = \mathbb{1}\Big[V_j(p;\theta_j) \geq V_f(q;\theta_f)\Big]$ as

$$D_{j,f}(p,q;i) = \mathbb{1}\Big[\delta(\theta_j^{[1]})\ p + \gamma(\theta_j) \geq \delta(\theta_f^{[1]})\ q + \gamma(\theta_f)\Big]. \tag{B.1}$$

Because $\theta \in \tilde{\Theta}_i$, $\delta(\theta_f^{[1]}) = 1$ and $\gamma(\theta_f) = 0$, so

$$D_{j,f}(p,q;i) = \mathbb{1}\Big[\delta(\theta_j^{[1]})\ p + \gamma(\theta_j) \geq q\Big]. \tag{B.2}$$

Define

$$Q_l(j,j',p) \equiv \Big\{q \ \Big|\ (j,j',p,q) \in \mathcal{V} \text{ and } D_{j,j'}(p,q;i) = 1\Big\}, \tag{B.3}$$

$$Q_u(j,j',p) \equiv \Big\{q \ \Big|\ (j,j',p,q) \in \mathcal{V} \text{ and } D_{j,j'}(p,q;i) = 0\Big\}, \tag{B.4}$$

with $q_{l,(j,j')}(p;i) \equiv \sup_q Q_l(j,j',p)$, $q_{u,(j,j')}(p;i) \equiv \inf_q Q_u(j,j',p)$ by definition (see (21) and (22)).

Equation (C.8) holds for all $(j, f, p, q) \in \mathcal{V}$ if and only if for all $(j, f) \in \mathcal{S}_f, p \in P_{j,f}$

$$q \leq \delta(\theta_j^{[1]})\ p + \gamma(\theta_j) \qquad \forall\ q \in Q_l(j, f, p) \tag{B.5}$$

and

$$q \geq \delta(\theta_j^{[1]})\ p + \gamma(\theta_j) \qquad \forall\ q \in Q_u(j, f, p), \tag{B.6}$$

with equations (C.9) and (C.10) holding if and only if for all $(j, f) \in \mathcal{S}_f, p \in P_{j,f}$

$$q_{l,(j,f)}(p; i) \leq \delta(\theta_j^{[1]})\ p + \gamma(\theta_j) \tag{B.7}$$

and

$$q_{u,(j,f)}(p; i) \geq \delta(\theta_j^{[1]})\ p + \gamma(\theta_j). \tag{B.8}$$

This completes the proof.

□

We now prove Theorem 1.

Proof of Theorem 1. We first show that θ_i is in the set given by (26). Because θ_i satisfies Assumption 1, $\theta_i \in \tilde{\Theta}_i$ and $D_{j,f}(p, q; i) = \mathbb{1}\left[V_j(p; \theta_{ij}) \geq V_f(q; \theta_{i,f})\right]$ for all $(j, f, p, q) \in \mathcal{V}$. Then by applying Lemma B.1 to θ_i, it follows that $\delta(\theta_{ij}^{[1]})\ p + \gamma(\theta_{ij}) \in \left[q_{l,(j,f)}(p; i), q_{u,(j,f)}(p; i)\right]$ for any $(j, f) \in \mathcal{S}_f, p \in P_{j,f}$.

We now show that the set given by (26) is equal to $\Theta_i^\star(\mathcal{S}_f)$. Inspecting the definition of $\Theta_i^\star(\mathcal{S}_f)$ as given by (18) and applying Lemma B.1 to any candidate θ, $\Theta_i^\star(\mathcal{S}_f)$ is equivalent to the set

$$\left\{\theta \in \tilde{\Theta}_i \;\middle|\; \delta(\theta_j^{[1]})\ p + \gamma(\theta_j) \in \left[q_{l,(j,f)}(p; i), q_{u,(j,f)}(p; i)\right]\ \forall (j, f) \in \mathcal{S}_f, p \in P_{j,f}\right\}. \tag{B.9}$$

Note that the constraints imposed on subvector θ_j for any θ in (C.13) do not impose any restrictions on subvector θ_{-j}. Thus the set in (C.13) is equivalent to the set given by (26). By Definition 5, it follows that the $\mathcal{S}_f$-sharp identified set for θ_i is given by the set in (26). □

Proof of Theorem 2. Result 1. follows directly from Theorem 1 and from the definitions of $\mathcal{B}_{i,(j,f)}$, the specification of Θ in (7), and the fact that Θ is a product space of $j-$specific parameter spaces. We now prove Result 2.

Proof of Result 2.

For any $j \in \mathcal{J} \setminus \{f, pr\}$, $\mathcal{B}_{i,(j,f)}^{[1]}$ and $\mathcal{B}_{i,(j,f)}^{[2]}$ are defined as

$$\mathcal{B}_{i,(j,f)}^{[1]} = \left\{\delta \in A_{ij} \mid \exists \gamma \in \mathbb{R} \text{ s.t. } \delta p + \gamma \in \left[q_{l,(j,f)}(p; i), q_{u,(j,f)}(p; i)\right] \quad \forall p \in P_{j,f}\right\}, \tag{B.10}$$

$$\mathcal{B}_{i,(j,f)}^{[2]} = \left\{\gamma \in \mathbb{R} \mid \exists \delta \in A_{ij} \text{ s.t. } \delta p + \gamma \in \left[q_{l,(j,f)}(p; i), q_{u,(j,f)}(p; i)\right] \quad \forall p \in P_{j,f}\right\}. \tag{B.11}$$

Let $\bar{\beta}_j(\theta) = \beta(\theta_j)$. Observe that $\delta_{ij} = \bar{\beta}_j(\theta_i)^{[1]}$ and $\gamma_{ij} = \bar{\beta}_j(\theta_i)^{[2]}$. To show that $\mathcal{B}_{i,(j,f)}^{[1]}$ and $\mathcal{B}_{i,(j,f)}^{[2]}$ are $\mathcal{S}_f$-sharp for these respective parameters, we need to show $\mathcal{B}_{i,(j,f)}^{[1]} = \bar{\beta}_j(\Theta_i^\star(\mathcal{S}_f))^{[1]}$ and $\mathcal{B}_{i,(j,f)}^{[2]} = \bar{\beta}_j(\Theta_i^\star(\mathcal{S}_f))^{[2]}$.

Since $\Theta_i^\star(\mathcal{S}_f)$ is the product space of $j-$specific sets, $\bar{\beta}_j(\Theta_i^\star(\mathcal{S}_f))$ can be written as:

$$\bar{\beta}_j(\Theta_i^\star(\mathcal{S}_f)) = \left\{(\delta_j,\gamma_j) \in \beta(\tilde{\Theta}_{ij}) \,\middle|\, \delta_j \; p + \gamma_j \in \left[q_{l,(j,f)}(p;i), q_{u,(j,f)}(p;i)\right] \quad \forall p \in P_{j,f}\right\}. \tag{B.12}$$

Because Θ is a product space, the projections of $\bar{\beta}_j(\Theta_i^\star(\mathcal{S}_f))$ onto its 1st and 2nd component are:

$$\begin{aligned}\bar{\beta}_j(\Theta_i^\star(\mathcal{S}_f))^{[1]} = \Big\{\delta_j \in \delta(\tilde{\Theta}_{ij}) \,\Big|\, & \exists \gamma_j \in \gamma(\tilde{\Theta}_{ij}) \text{ s.t.} \\ & \delta_j \; p + \gamma_j \in \left[q_{l,(j,f)}(p;i), q_{u,(j,f)}(p;i)\right] \quad \forall p \in P_{j,f}\Big\},\end{aligned} \tag{B.13}$$

$$\begin{aligned}\bar{\beta}_j(\Theta_i^\star(\mathcal{S}_f))^{[2]} = \Big\{\gamma_j \in \gamma(\tilde{\Theta}_{ij}) \,\Big|\, & \exists \delta_j \in \delta(\tilde{\Theta}_{ij}) \text{ s.t.} \\ & \delta_j \; p + \gamma_j \in \left[q_{l,(j,f)}(p;i), q_{u,(j,f)}(p;i)\right] \quad \forall p \in P_{j,f}\Big\}.\end{aligned} \tag{B.14}$$

Thus, to show that $\mathcal{B}^{[1]}_{i,(j,f)} = \bar{\beta}_j(\Theta_i^\star(\mathcal{S}_f))^{[1]}$ and $\mathcal{B}^{[2]}_{i,(j,f)} = \bar{\beta}_j(\Theta_i^\star(\mathcal{S}_f))^{[2]}$ for any $j \in \mathcal{J} \setminus \{f, pr\}$, it is sufficient to show that $\delta(\tilde{\Theta}_{ij}) = A_{ij}$ and $\gamma(\tilde{\Theta}_{ij}) = \mathbb{R}$ for any $j \in \mathcal{J} \setminus \{f, pr\}$, where $\delta(\theta_j) = \pi_j\mu_j$ and $\gamma(\theta_j) = \pi_j\eta_j(1) + (1-\pi_j)\eta_j(0) + c_j$. This follows from inspection of $\tilde{\Theta}_{ij}$ (and thus Θ_j as defined in (7)) and A_{ij} for $j \in \mathcal{J} \setminus \{f, pr\}$.

We now show that $\mathcal{B}^{[1]}_{i,(j,f)}$ and $\mathcal{B}^{[2]}_{i,(j,f)}$ are intervals for any $j \in \mathcal{J} \setminus \{f, pr\}$. Consider any $j \in \mathcal{J} \setminus \{f, pr\}$. If either $\mathcal{B}^{[1]}_{i,(j,f)}$ or $\mathcal{B}^{[2]}_{i,(j,f)}$ are singletons, they are trivially intervals. We will thus assume that there exist at least two distinct points in $\mathcal{B}^{[1]}_{i,(j,f)}$ and $\mathcal{B}^{[2]}_{i,(j,f)}$.

Let $\delta_1, \delta_2 \in \mathcal{B}^{[1]}_{i,(j,f)}$ with $\delta_1 \neq \delta_2$. Without loss of generality, suppose $\delta_1 < \delta_2$. By definition of $\mathcal{B}^{[1]}_{i,(j,f)}$, $0 \leq \delta_1$. There must exist corresponding γ_1, γ_2 such that $(\delta_1,\gamma_1),(\delta_2,\gamma_2) \in \mathcal{B}_{i,(j,f)}$. Let p^* denote the intersection point between the lines $\delta_1 p + \gamma_1$ and $\delta_2 p + \gamma_2$:

$$p^* = \frac{\gamma_1 - \gamma_2}{\delta_2 - \delta_1}. \tag{B.15}$$

Consider any δ^* such that $\delta_1 < \delta^* < \delta_2$. Define γ^* so that the line $\delta^* p + \gamma^*$ intersects $\delta_1 p + \gamma_1$ and $\delta_2 p + \gamma_2$ at $p = p^*$:

$$\gamma^* \equiv (\delta_2 - \delta^*)p^* + \gamma_2 = (\delta_1 - \delta^*)p^* + \gamma_1. \tag{B.16}$$

Then, using that $0 \leq \delta_1$:

$$q_{l,(j,f)}(p;i) \leq \delta_2 p + \gamma_2 \leq \delta^* p + \gamma^* \leq \delta_1 p + \gamma_1 \leq q_{u,(j,f)}(p;i) \;\; \forall p < p^* \tag{B.17}$$

$$q_{l,(j,f)}(p;i) \leq \delta_1 p + \gamma_1 \leq \delta^* p + \gamma^* \leq \delta_2 p + \gamma_2 \leq q_{u,(j,f)}(p;i) \;\; \forall p \geq p^*. \tag{B.18}$$

So for any $p \in P_{j,f}$, $\delta^* p + \gamma^* \in [q_{l,(j,f)}(p;i), q_{u,(j,f)}(p;i)]$. Because A_{ij} is an interval for all j, $\delta^* \in [\delta_1, \delta_2] \subseteq A_{ij}$. Trivially, $\gamma^* \in \mathbb{R}$. We conclude that $\delta^* \in \mathcal{B}^{[1]}_{i,(j,f)}$.

Similarly, let $\gamma_1, \gamma_2 \in \mathcal{B}^{[2]}_{i,(j,f)}$ with $\gamma_1 \neq \gamma_2$ be arbitrary. Without loss of generality, suppose $\gamma_1 < \gamma_2$. Consider any γ^* such that $\gamma_1 < \gamma^* < \gamma_2$. There must exist corresponding δ_1, δ_2 such that $(\delta_1,\gamma_1),(\delta_2,\gamma_2) \in \mathcal{B}_{i,(j,f)}$.

Case 1: $\delta_1 = \delta_2$. Then $q_{l,(j,f)}(p;i) \leq \delta_1 p + \gamma_1 \leq \delta_1 p + \gamma^* \leq \delta_2 p + \gamma_2 \leq q_{u,(j,f)}(p;i)$. Because $\gamma^* \in \mathbb{R}$ and $\delta_1 \in A_{ij}$, we conclude $\gamma^* \in \mathcal{B}^{[2]}_{i,(j,f)}$.

Case 2: $\delta_1 \neq \delta_2$. Then there must exist an intersection point p^* between the lines $\delta_1 p + \gamma_1$ and $\delta_2 p + \gamma_2$, as before:

$$p^* = \frac{\gamma_1 - \gamma_2}{\delta_2 - \delta_1}. \tag{B.19}$$

Note $p^* \neq 0$ because $\gamma_1 \neq \gamma_2$. Define δ^* so that the line $\delta^* p + \gamma^*$ intersects $\delta_1 p + \gamma_1$ and $\delta_2 p + \gamma_2$ at $p = p^*$:

$$\delta^* \equiv \delta_2 + \frac{\gamma_2 - \gamma^*}{p^*} = \delta_1 + \frac{\gamma_1 - \gamma^*}{p^*}. \tag{B.20}$$

Note that if $\delta_2 > \delta_1$ then $p^* < 0$. Because $\gamma_2 - \gamma^* > 0$ and $\gamma_1 - \gamma^* < 0$, $\delta_1 < \delta^* < \delta_2$. If $\delta_2 < \delta_1$, then $p^* > 0$, so that $\delta_2 < \delta^* < \delta_1$. Thus by an analogous argument to the proof for $\mathcal{B}^{[1]}_{i,(j,f)}$, $\delta^* p + \gamma^* \in [q_{l,(j,f)}(p;i), q_{u,(j,f)}(p;i)]$ for any $p \in P_{j,f}$. Because $\delta_1, \delta_2 \in A_{ij}$ by assumption and $\delta^* \in [\delta_1, \delta_2]$, we have that $\delta^* \in A_{ij}$. Because $\gamma^* \in \mathbb{R}$, we conclude $\gamma^* \in \mathcal{B}^{[2]}_{i,(j,f)}$.

$\square$

Proof of Theorem 3. Proof of Result 1.

Let $\bar{\lambda}_j(\theta) = \lambda(\theta_j)$. From Theorem 2, $[\delta_{ij,l}, \delta_{ij,u}]$ and $[\gamma_{ij,l}, \gamma_{ij,u}]$ are $\mathcal{S}_f$-sharp for $\delta(\theta^{[1]}_{ij})$ and $\gamma(\theta_{ij})$. It suffices to consider the bounds that are not singletons, as the singleton bounds are trivially equal to the respective kth projections of $\bar{\lambda}_j\left(\Theta^\star_i(\mathcal{S}_f)\right)$ by inspection of $\tilde{\Theta}_i$. Note that $\bar{\lambda}_j\left(\Theta^\star_i(\mathcal{S}_f)\right)^{[k]}$ is the $\mathcal{S}_f$-sharp identified set for the kth component of $\lambda(\theta_{ij})$. By inspection of the non-singleton bounds in Table 1, it is clear that these are outer sets for the $\mathcal{S}_f$-sharp identified sets. Thus, it suffices to show that the $\mathcal{S}_f$-sharp identified sets contain these bounds. We proceed by considering each scheme separately.

Suppose $j = (pt, k)$. We first consider the bounds for π_{ij}. For any $d \in [\delta_{ij,l}, \delta_{ij,u}]$, there exists $\theta \in \Theta^\star_i(\mathcal{S}_f)$ such that $\delta(\theta^{[1]}_j) = \pi_j \mu_j = d$. The constraints given $\theta \in \Theta^\star_i(\mathcal{S}_f) \subseteq \tilde{\Theta}_i$ imply that $\mu_j = S^*_{ij}$, so that $\pi_j = d/S^*_{ij}$. Since this holds for any d, it follows that the $\mathcal{S}_f$-sharp identified set for π_{ij} contains $[\delta_{ij,l}/S^*_{ij}, \delta_{ij,u}/S^*_{ij}]$, which are the bounds listed in Table 1. Next, consider the bounds for ψ_{ij}. For any $g \in [\gamma_{ij,l}, \gamma_{ij,u}]$, there exists $\theta \in \Theta^\star_i(\mathcal{S}_f)$ such that $\gamma(\theta_j) = g$. Since it must hold that $c_j = 0$ for θ, it follows that $g = \psi(\theta_j) + c_j = \psi(\theta_j)$, so that the $\mathcal{S}_f$-sharp identified set for ψ_{ij} contains $[\gamma_{ij,l}, \gamma_{ij,u}]$, which are the bounds listed in Table 1.

Suppose $j = fr$. For μ_{ij}, for any $d \in [\delta_{ij,l}, \delta_{ij,u}]$, there exists $\theta \in \Theta^\star_i(\mathcal{S}_f)$ with $\pi_j = 1$ so that $\pi_j \mu_j = \mu_j = d$, so that the $\mathcal{S}_f$-sharp identified set contains $[\delta_{ij,l}, \delta_{ij,u}]$. For c_{ij}, for any $g \in [\gamma_{ij,l}, \gamma_{ij,u}]$, there exists $\theta \in \Theta^\star_i(\mathcal{S}_f)$ with $\psi(\theta_j) = 0$ so that $\psi(\theta_j) + c_j = c_j = g$, so that the $\mathcal{S}_f$-sharp identified set contains $[\gamma_{ij,l}, \gamma_{ij,u}]$.

Suppose $j = ft$. We first consider bounds on μ_{ij}. For any $d \in [\delta_{ij,l}, \delta_{ij,u}]$, there exists some $\theta \in \Theta^\star_i(\mathcal{S}_f)$ such that $\delta(\theta^{[1]}_j) = \pi_j \mu_j = d$ and

$$\gamma(\theta_j) = \pi_j \eta_j(1) + (1 - \pi_j)\eta_j(0) + c_j \equiv g.$$

For any $\alpha \in (0, 1]$, construct $\tilde{\theta}$ that is equal to θ except that $\tilde{\pi}_j = \alpha$, $\tilde{\mu}_j = d/\alpha$ and $\tilde{c}_j = c_j + (\pi_j - \tilde{\pi}_j)\eta_j(1) + ((1 - \pi_j) - (1 - \tilde{\pi}_j))\eta_j(0)$. By construction, $\tilde{\theta} \in \tilde{\Theta}_i$, $\delta(\tilde{\theta}^{[1]}_j) = d$ and $\gamma(\tilde{\theta}_j) = g$. Note that for all schemes $j' \neq ft$, $\tilde{\theta}_{j'} = \theta_{j'}$. Thus by inspection of the definition of $\Theta^\star_i(\mathcal{S}_f)$, $\tilde{\theta} \in \Theta^\star_i(\mathcal{S}_f)$. Since this construction holds for any $(d, \alpha) \in [\delta_{ij,l}, \delta_{ij,u}] \times (0, 1]$, it follows that the $\mathcal{S}_f$-sharp identified set for μ_{ij} contains $[\delta_{j,l}, \infty)$.

We use a slightly different approach for the rest of the parameters under the case where $j = ft$.

Consider π_{ij}. If $\delta_{ij} = 0$, then for any $\alpha \in [0, 1]$ construct θ that is equal to θ_i except that $\pi_j = \alpha$, $\mu_j = 0$, and

$$c_j = c_{ij} + (\pi_{ij} - \pi_j)\eta_{ij}(1) + ((1 - \pi_{ij}) - (1 - \pi_j))\eta_{ij}(0).$$

If $\delta_{ij} \neq 0$, then for any $\alpha \in (0,1]$ construct θ that is equal to θ_i except that $\pi_j = \alpha$, $\mu_j = \frac{\delta_{ij}}{\alpha}$, and

$$c_j = c_{ij} + (\pi_{ij} - \pi_j)\eta_{ij}(1) + ((1-\pi_{ij}) - (1-\pi_j))\eta_{ij}(0).$$

Since the components of θ are equal to those of θ_i except for π_j, μ_j, and c_j, and since we have that $\pi_j \in [0,1]$ and $\mu_j \geq 0$ because $\delta_{ij} \geq 0$, it follows from inspection of Θ that $\theta \in \tilde{\Theta}_i$. Also, we have $\delta(\theta_{j'}^{[1]}) = \delta_{ij'}$ and $\gamma(\theta_{j'}) = \gamma_{ij'}$ for all $j' \neq j$. By construction, $\delta(\theta_j^{[1]}) = \delta_{ij}$ and $\gamma(\theta_j) = \gamma_{ij}$. Since $\theta_i \in \Theta_i^\star(\mathcal{S}_f)$, by inspection of the definition of $\Theta_i^\star(\mathcal{S}_f)$, $\theta \in \Theta_i^\star(\mathcal{S}_f)$. If $0 \in \delta(\Theta_i^\star(\mathcal{S}_f))$, because $\delta_{ij} \in \delta(\Theta_i^\star(\mathcal{S}_f))$ then it is possible that $\delta_{ij} = 0$. If $0 \notin \delta(\Theta_i^\star(\mathcal{S}_f))$, because $\delta_{ij} \in \delta(\Theta_i^\star(\mathcal{S}_f))$ then we know $\delta_{ij} \neq 0$. So the $\mathcal{S}_f$-sharp identified set for π_{ij} is $[0,1]$ if $0 \in \delta(\Theta_i^\star(\mathcal{S}_f))$ and $(0,1]$ otherwise.

For the bounds on ψ_{ij} and c_{ij}, for any $\epsilon \in \mathbb{R}$ construct a vector θ whose components are equal to θ_i except that $c_j = c_{ij} + \epsilon$ and choose $(\eta_j(0), \eta_j(1)) \in \mathbb{R}^2$ so that

$$\pi_{ij}\eta_j(1) + (1-\pi_{ij})\eta_j(0) = \pi_{ij}\eta_{ij}(1) + (1-\pi_{ij})\eta_{ij}(0) - \epsilon,$$

which can always be done since at least one of π_{ij} or $(1-\pi_{ij})$ is non-zero. Then $\psi(\theta_j) = \psi(\theta_{ij}) - \epsilon$ and $\gamma(\theta_j) = \gamma(\theta_{ij})$. Since the components of θ are equal to those of θ_i except for $\eta_j(0), \eta_j(1)$, and c_j, it follows from inspection of Θ that $\theta \in \tilde{\Theta}_i$. It also follows that $\delta(\theta_{j'}^{[1]}) = \delta(\theta_{ij'}^{[1]})$ for all $j' \in \mathcal{J}$ and $\gamma(\theta_{j'}) = \gamma(\theta_{ij'})$ for all $j' \in \mathcal{J}$ such that $j' \neq ft$. Since $\theta_i \in \Theta_i^\star(\mathcal{S}_f)$, by inspection of the definition of $\Theta_i^\star(\mathcal{S}_f)$, $\theta \in \Theta_i^\star(\mathcal{S}_f)$. It follows that $c_j = c_{ij} + \epsilon$ is in the sharp identified set for c_{ij} and $\psi(\theta_j) = \psi(\theta_{ij}) - \epsilon$ is in the sharp identified set for $\psi(\theta_{ij})$. Because this holds for any $\epsilon \in \mathbb{R}$, the $\mathcal{S}_f$-sharp identified sets for c_{ij} and ψ_{ij} are both $(-\infty, \infty)$.

Finally, suppose $j = fl$. For the bounds on π_{ij}, we employ the exact same approach as for the case where $j = (pt, k)$ with $S_{ij}^* = 1$. For the bounds on ψ_{ij} and c_{ij}, we employ the same approach as for the case where $j = ft$.

Proof of Result 2.

We showed in the proof of Result 1. that the bounds presented in Table 1 for $\pi_{i,ft}, \psi_{i,ft}$, $\psi_{i,fl}$, and $c_{i,ft}$ are the $\mathcal{S}_f$-sharp identified sets. We will show that the sharp identified sets for those parameters are equal to the $\mathcal{S}_f$-sharp identified sets.

Following Remark 3.2 and Definition 5, the sharp identified set for θ_i can be written as

$$\Theta_i^\star = \left\{\theta \in \tilde{\Theta}_i \;\middle|\; D_{j,j'}(p,q;i) = \mathbb{1}\left[\delta(\theta_j^{[1]})\ p + \gamma(\theta_j) \geq \delta(\theta_{j'}^{[1]})\ q + \gamma(\theta_{j'})\right]\ \ \forall\ (j,j',p,q) \in \mathcal{V}\right\}. \tag{B.21}$$

Let $\theta \in \Theta_i^\star$. Inspecting (B.21), it is clear that if for some candidate $\tilde{\theta}$ it holds that $\tilde{\theta} \in \tilde{\Theta}_i$, $\delta(\tilde{\theta}_j^{[1]}) = \delta(\theta_j^{[1]})$ for all $j \in \mathcal{J}$, and $\gamma(\tilde{\theta}_j) = \gamma(\theta_j)$ for all $j \in \mathcal{J}$, it must follow that $\tilde{\theta} \in \Theta_i^\star$ as well. We showed in the proof of Result 1. that for $\pi_{i,ft}, \psi_{i,ft}$, $\psi_{i,fl}$, and $c_{i,ft}$, it is possible to construct some candidate θ such that $\theta \in \tilde{\Theta}_i$, $\delta(\theta_j^{[1]}) = \delta_{ij}$ for all $j \in \mathcal{J}$, and $\gamma(\theta_j) = \gamma_{ij}$ for all $j \in \mathcal{J}$. Since $\theta_i \in \Theta_i^\star$ by definition of an identified set, it follows that the candidate $\theta \in \Theta_i^\star$.

Thus the bounds presented in Table 1 for $\pi_{i,ft}, \psi_{i,ft}$, $\psi_{i,fl}$, $c_{i,ft}$ are the sharp identified sets and inspection of $\tilde{\Theta}_i$ establishes that these bounds are uninformative (up to taking the closure of the bounds on $\pi_{i,ft}$). It remains to show that the sharp identified set for $\mu_{i,ft}$ is unbounded above.

Let $x > \mu_{i,ft}$ be arbitrary. Construct a vector θ whose components are equal to θ_i except for $\mu_{ft} = x$ and $\pi_{ft} = \frac{\delta(\theta_{i,ft}^{[1]})}{x}$. Note that this is well-defined because $\mu_{i,ft} \geq 0$ and thus $x > \mu_{i,ft} \geq 0$. Since the components of θ are equal to those of θ_i except for π_{ft} and μ_{ft}, it follows that $\gamma(\theta_j) = \gamma(\theta_{ij})$ for all $j \in \mathcal{J}$ and $\delta(\theta_j^{[1]}) = \delta(\theta_{ij}^{[1]})$ for all $j \in \mathcal{J}$ except for $j = ft$. For

$j = ft$, $\delta(\theta_{ft}^{[1]}) = \pi_{ft}\mu_{ft} = \delta(\theta_{i,ft}^{[1]})$.

Note that $\pi_{ft} = \frac{\delta(\theta_{i,ft}^{[1]})}{x} = \frac{\pi_{i,ft}\mu_{i,ft}}{x}$. $x > \mu_{i,ft}$ implies that $\mu_{ft} \geq 0$ and $\pi_{ft} < \pi_{i,ft} \leq 1$. Since $\pi_{i,ft} \geq 0$ and $x > \mu_{i,ft} \geq 0$, it follows that $\pi_{ft} \geq 0$ and thus $\pi_{ft} \in [0,1]$. Thus $\theta \in \tilde{\Theta}_i$. Because we showed that $\delta(\theta_j^{[1]}) = \delta(\theta_{ij}^{[1]})$ and $\gamma(\theta_j) = \gamma(\theta_{ij})$ for all $j \in \mathcal{J}$, it follows that $\theta \in \Theta_i^\star$, so $\mu_{ft} = x$ is in the sharp identified set for $\mu_{i,ft}$. Because this holds for any $x > \mu_{i,ft}$, we can take x as large as we want and thus the sharp identified set for $\mu_{i,ft}$ must be unbounded.

□

We now formally state and prove the claim of Remark 4.2.

Proposition B.1 (Formal statement of Remark 4.2). *Suppose individual i satisfies Assumption 1. Let $[\delta_{ij,l},\ \delta_{ij,u}]$ and $[\gamma_{ij,l},\ \gamma_{ij,u}]$ be defined as in Theorem 2. A necessary condition for $[\delta_{ij,l},\ \delta_{ij,u}]$ to be informative is that $|P_{j,f}| \geq 2$. A sufficient condition for this interval and for $[\gamma_{ij,l},\ \gamma_{ij,u}]$ to both be bounded and informative is that there exists $p_1, p_2 \in P_{j,f}$ with $p_2 > p_1$ such that*

$$\frac{\Big(q_{u,(j,f)}(p_2;i) - q_{l,(j,f)}(p_2;i)\Big) + \Big(q_{u,(j,f)}(p_1;i) - q_{l,(j,f)}(p_1;i)\Big)}{p_2 - p_1} < \sup A_{ij} - \inf A_{ij}. \tag{B.22}$$

Proof of Proposition B.1. We first show the necessary condition is necessary. Fix $j \in \mathcal{J} \setminus \{f, pr\}$ and suppose $|P_{j,f}| = 1$. Let p denote the single value in $P_{j,f}$. By Theorem 2,

$$[\delta_{ij,l}, \delta_{ij,u}] = \left\{\delta \in A_{ij} \;\middle|\; \exists \gamma \in \mathbb{R} \text{ s.t. } \delta p + \gamma \in [q_{l,(j,f)}(p;i), q_{u,(j,f)}(p;i)]\right\}. \tag{B.23}$$

In the proof of Theorem 2, we showed $[\delta_{ij,l}, \delta_{ij,u}]$ is uninformative if $[\delta_{ij,l}, \delta_{ij,u}] = A_{ij}$, so it suffices to show $A_{ij} \subseteq [\delta_{ij,l}, \delta_{ij,u}]$. Consider arbitrary $d \in A_{ij}$. Let g be any value in the interval $[q_{l,(j,f)}(p;i) - dp, q_{u,(j,f)}(p;i) - dp]$. By construction, $q_{l,(j,f)}(p;i) \leq dp + g \leq q_{u,(j,f)}(p;i)$ and $g \in \mathbb{R}$. Thus $d \in [\delta_{ij,l}, \delta_{ij,u}]$, as required.

We now show the sufficient condition is sufficient. Fix $j \in \mathcal{J} \setminus \{f, pr\}$ and suppose that there exists distinct $p_1, p_2 \in P_{j,f}$ with $p_2 > p_1$ (and recalling that these values are strictly positive) such that

$$\frac{\Big(q_{u,(j,f)}(p_2;i) - q_{l,(j,f)}(p_2;i)\Big) + \Big(q_{u,(j,f)}(p_1;i) - q_{l,(j,f)}(p_1;i)\Big)}{p_2 - p_1} < \sup A_{ij} - \inf A_{ij}. \tag{B.24}$$

We want to show that both $[\delta_{ij,l}, \delta_{ij,u}]$ and $[\gamma_{ij,l}, \gamma_{ij,u}]$ are bounded and informative. From the above, $[\delta_{ij,l}, \delta_{ij,u}]$ is informative if it is a strict subset of A_{ij}, and $[\gamma_{ij,l}, \gamma_{ij,u}]$ is informative if it is a strict subset of $\mathbb{R}$.

Consider any $d \in [\delta_{ij,l}, \delta_{ij,u}]$. There thus exists some g such that

$$q_{l,(j,f)}(p_k;i) \leq d\ p_k + g \leq q_{u,(j,f)}(p_k;i) \tag{B.25}$$

for $k = 1, 2$. Re-arranging these inequalities, we have that

$$q_{l,(j,f)}(p_2;i) - g \leq d\ p_2 \leq q_{u,(j,f)}(p_2;i) - g \tag{B.26}$$

and

$$q_{l,(j,f)}(p_1;i) - d\ p_1 \leq g \leq q_{u,(j,f)}(p_1;i) - d\ p_1. \tag{B.27}$$

Combining these two inequalities and simplifying yields

$$\frac{q_{l,(j,f)}(p_2;i) - q_{u,(j,f)}(p_1;i)}{p_2 - p_1} \leq d \leq \frac{q_{u,(j,f)}(p_2;i) - q_{l,(j,f)}(p_1;i)}{p_2 - p_1}. \tag{B.28}$$

Since $d \in [\delta_{ij,l}, \delta_{ij,u}]$ implies that $d \in A_{ij}$, and since A_{ij} is a connected set, $d \in [\inf A_{ij}, \sup A_{ij}]$. Thus,

$$d \in [\inf A_{ij}, \sup A_{ij}] \cap \left[\frac{q_{l,(j,f)}(p_2;i) - q_{u,(j,f)}(p_1;i)}{p_2 - p_1}, \frac{q_{u,(j,f)}(p_2;i) - q_{l,(j,f)}(p_1;i)}{p_2 - p_1}\right] \subseteq A_{ij}, \tag{B.29}$$

and the subset inclusion holds strictly because the second interval has width

$$\frac{\Big(q_{u,(j,f)}(p_2;i) - q_{l,(j,f)}(p_2;i)\Big) - \Big(q_{u,(j,f)}(p_1;i) - q_{l,(j,f)}(p_1;i)\Big)}{p_2 - p_1} < \sup A_{ij} - \inf A_{ij} \tag{B.30}$$

by assumption. Since this holds for any d in the proposed bounds, and since the set in (B.29) is independent of d, we have shown that $[\delta_{ij,l}, \delta_{ij,u}]$ is informative and bounded.

Now consider any $g \in [\gamma_{ij,l}, \gamma_{ij,u}]$. We know there must exist an associated $d \in A_{ij}$ so that

$$q_{l,(j,f)}(p_k;i) \leq d\ p_k + g \leq q_{u,(j,f)}(p_k;i) \tag{B.31}$$

for $k = 1, 2$. Rewriting for $k = 1$, we have that

$$g \in \left[q_{l,(j,f)}(p_k;i) - d\ p_1, q_{u,(j,f)}(p_k;i) - d\ p_1\right] \tag{B.32}$$

Because this holds for any $g \in [\gamma_{ij,l}, \gamma_{ij,u}]$, it follows that

$$[\gamma_{ij,l}, \gamma_{ij,u}] \subseteq \left[q_{l,(j,f)}(p_k;i) - d\ p_1, q_{u,(j,f)}(p_k;i) - d\ p_1\right]. \tag{B.33}$$

Equation (B.24) implies that $\left[q_{l,(j,f)}(p_k;i), q_{u,(j,f)}(p_k;i)\right]$ is bounded. $\left[q_{l,(j,f)}(p_k;i) - d\ p_1, q_{u,(j,f)}(p_k;i) - d\ p_1\right]$ must also be bounded because d and p_1 are finite. Thus $[\gamma_{ij,l}, \gamma_{ij,u}]$ is bounded and informative, as required. □

Appendix C $\mathcal{S}$-sharp identified sets

In this appendix we provide results for sharp identified sets of target parameters that are sharp relative to the entire set of scheme choices $\mathcal{S}$. As discussed in Subsection 4.1, we can check if the model with a candidate parameter value θ is consistent with all observed choices by checking if θ is consistent with the payoff indifference sets. The following theorem uses this observation to generalize Theorem 1, which provides $\mathcal{S}_f$-sharp identified sets, to identified sets that are sharp relative to $\mathcal{S}$.

Theorem C.1. *Suppose individual i satisfies Assumption 1. For any $(j,j') \in \mathcal{S},\ p \in P_{j,j'}$, define:*

$$\begin{aligned}
\Theta^{[a]}_{i,(j,j',p)} &= \Bigg\{\theta \in \mathbb{R}^K \ \Bigg|\ \delta(\theta^{[1]}_{j'}) \neq 0 \\
&\qquad \& \ \ q_{l,(j,j')}(p;i) \leq \frac{1}{\delta(\theta^{[1]}_{j'})}\Big(\delta(\theta^{[1]}_{j})\ p + \gamma(\theta_j) - \gamma(\theta_{j'})\Big) \leq q_{u,(j,j')}(p;i)\Bigg\},\\
\Theta^{[b]}_{i,(j,j',p)} &= \Bigg\{\theta \in \mathbb{R}^K \ \Bigg|\ \delta(\theta^{[1]}_{j'}) = 0 \ \ \& \ \ q_{u,(j,j')}(p;i) = \infty \ \ \& \ 0 \leq \delta(\theta^{[1]}_{j})\ p + \gamma(\theta_j) - \gamma(\theta_{j'})\Bigg\},\\
\Theta^{[c]}_{i,(j,j',p)} &= \Bigg\{\theta \in \mathbb{R}^K \ \Bigg|\ \delta(\theta^{[1]}_{j'}) = 0 \ \ \& \ \ q_{l,(j,j')}(p;i) = -\infty \ \& \ 0 \geq \delta(\theta^{[1]}_{j})\ p + \gamma(\theta_j) - \gamma(\theta_{j'})\Bigg\}.
\end{aligned}$$

Then, for any $\mathcal{S}' \subseteq \mathcal{S}$ and target parameter $\tau_i^\star$, $\theta_i \in \Theta_i^\star(\mathcal{S}')$ and thus $\tau_i^\star \in \tau\left(\Theta_i^\star(\mathcal{S}')\right)$, where

$$\Theta_i^\star(\mathcal{S}') \equiv \left(\bigcap_{(j,j')\in\mathcal{S}'}\ \bigcap_{p\in P_{j,j'}} \left(\Theta^{[a]}_{i,(j,j',p)} \ \cup\ \Theta^{[b]}_{i,(j,j',p)} \ \cup\ \Theta^{[c]}_{i,(j,j',p)}\right)\right) \ \bigcap\ \tilde{\Theta}_i. \tag{C.1}$$

Furthermore, $\Theta_i^\star(\mathcal{S})$ is the sharp identified set for θ_i, $\Theta_i^\star(\mathcal{S}) = \Theta_i^\star$, and thus $\tau(\Theta_i^\star(\mathcal{S})) = \tau(\Theta_i^\star)$.

Following the reasoning of Remark 3.2 we see that a parameter $\theta \in \tilde{\Theta}_i$ is consistent with the observed data for individual i if and only if $\{(\delta(\theta^{[1]}_j), \gamma(\theta_j))\}_{j\in\mathcal{J}}$ is consistent with the individual's choices. This observation leads us to the following dual to Theorem C.1.

Corollary C.1.1. *Suppose individual i satisfies Assumption 1. Define the function g implicitly via $\bar{\beta}(\theta) = g \ \circ\ \bar{\lambda}(\theta)$, and thus $\bar{\beta}^- = \bar{\lambda}^- \circ g^-$, where $f^-(B)$ denotes the preimage of set B under any function f, where B is a subset of the codomain of f. For any $(j,j') \in \mathcal{S},\ p \in P_{j,j'}$, define:*

$$\begin{aligned}
\mathcal{B}^{[a]}_{i,(j,j',p)} &= \Bigg\{\beta \in \mathbb{R}^{2|\mathcal{J}|} \ \Bigg|\ \delta_{j'} \neq 0 \ \ \& \ \ q_{l,(j,j')}(p;i) \leq \frac{1}{\delta_{j'}}\Big(\delta_j\ p + \gamma_j - \gamma_{j'}\Big) \leq q_{u,(j,j')}(p;i))\Bigg\},\\
\mathcal{B}^{[b]}_{i,(j,j',p)} &= \Bigg\{\beta \in \mathbb{R}^{2|\mathcal{J}|} \ \Bigg|\ \delta_{j'} = 0 \ \ \& \ \ q_{u,(j,j')}(p;i) = \infty \ \ \& \ 0 \leq \delta_j\ p + \gamma_j - \gamma_{j'}\Bigg\},\\
\mathcal{B}^{[c]}_{i,(j,j',p)} &= \Bigg\{\beta \in \mathbb{R}^{2|\mathcal{J}|} \ \Bigg|\ \delta_{j'} = 0 \ \ \& \ \ q_{l,(j,j')}(p;i) = -\infty \ \& \ 0 \geq \delta_j\ p + \gamma_j - \gamma_{j'}\Bigg\}.
\end{aligned}$$

Then, for any $\mathcal{S}' \subseteq \mathcal{S}$, define

$$\mathcal{B}_i(\mathcal{S}') \equiv \bigcap_{(j,j')\in\mathcal{S}'}\ \bigcap_{p\in P_{j,j'}} \ \left(\ \mathcal{B}^{[a]}_{i,(j,j',p)} \ \cup\ \mathcal{B}^{[b]}_{i,(j,j',p)} \ \cup\ \mathcal{B}^{[c]}_{i,(j,j',p)}\right).$$

Then:

1. $\Theta_i^\star(\mathcal{S}') = \bar{\beta}^-(\mathcal{B}_i(\mathcal{S}')) \cap \tilde{\Theta}_i$;
2. $\bar{\beta}(\Theta_i^\star(\mathcal{S}')) = \mathcal{B}_i(\mathcal{S}') \cap \bar{\beta}(\tilde{\Theta}_i)$;
3. $\bar{\lambda}(\Theta_i^\star(\mathcal{S}')) = g^-(\mathcal{B}_i(\mathcal{S}')) \cap \bar{\lambda}(\tilde{\Theta}_i)$.

Theorem C.1 and Corollary C.1.1 provide general identification results, including characterizations of the sharp identified sets. For any (j,k), the projections of $\mathcal{B}_i(\mathcal{S}')$ and $\tau(\Theta_i^\star(\mathcal{S}'))$ onto the jth scheme's kth component, which we respectively denote as $\mathcal{B}_i(\mathcal{S}')^{[j,k]}$ and $\tau(\Theta_i^\star(\mathcal{S}'))^{[j,k]}$, provide identified sets for our considered scalar target parameters. These sets are sharp for $\mathcal{S}' = \mathcal{S}$.

The following lemma will be useful for proving Theorem C.1.

Lemma C.2. *Given any* $(j, j', p, q) \in \mathcal{V}$*,* θ *satisfies* $D_{j,j'}(p, q; i) = \mathbb{1}\Big[V_j(p; \theta_j) \geq V_{j'}(q; \theta_{j'})\Big]$ *if and only if at least one of the following holds for* θ*:*

$$1.\ \ \delta(\theta_{j'}^{[1]}) \neq 0 \text{ and } q_{l,(j,j')}(p; i) \leq \frac{1}{\delta(\theta_{j'}^{[1]})}\Big(\delta(\theta_j^{[1]})\ p + \gamma(\theta_j) - \gamma(\theta_{j'})\Big) \leq q_{u,(j,j')}(p; i) \tag{C.2}$$

$$2.\ \ \delta(\theta_{j'}^{[1]}) = 0 \text{ and } q_{u,(j,j')}(p; i) = \infty \text{ and } 0 \leq \delta(\theta_j^{[1]})\ p + \gamma(\theta_j) - \gamma(\theta_{j'}) \tag{C.3}$$

$$3.\ \ \delta(\theta_{j'}^{[1]}) = 0 \text{ and } q_{l,(j,j')}(p; i) = -\infty \text{ and } 0 \geq \delta(\theta_j^{[1]})\ p + \gamma(\theta_j) - \gamma(\theta_{j'}) \tag{C.4}$$

Proof of Lemma C.2. Following Remark 3.2, we can rewrite $D_{j,j'}(p, q; i) = \mathbb{1}\Big[V_j(p; \theta_j) \geq V_{j'}(q; \theta_{j'})\Big]$ as

$$D_{j,j'}(p, q; i) = \mathbb{1}\Big[\delta(\theta_j^{[1]})\ p + \gamma(\theta_j) \geq \delta(\theta_{j'}^{[1]})\ q + \gamma(\theta_{j'})\Big]. \tag{C.5}$$

Define

$$Q_l(j, j', p) \equiv \Big\{q \ \Big|\ (j, j', p, q) \in \mathcal{V} \text{ and } D_{j,j'}(p, q; i) = 1\Big\}, \tag{C.6}$$

$$Q_u(j, j', p) \equiv \Big\{q \ \Big|\ (j, j', p, q) \in \mathcal{V} \text{ and } D_{j,j'}(p, q; i) = 0\Big\}, \tag{C.7}$$

and define $q_{l,(j,j')}(p; i) \equiv \sup_q Q_l(j, j', p)$, $q_{u,(j,j')}(p; i) \equiv \inf_q Q_u(j, j', p)$.

Case 1: Suppose $\delta(\theta_{j'}^{[1]}) \neq 0$. Then we can rewrite equation (C.5) as

$$D_{j,j'}(p, q; i) = \mathbb{1}\left[\frac{1}{\delta(\theta_{j'}^{[1]})}\Big(\delta(\theta_j^{[1]})\ p + \gamma(\theta_j) - \gamma(\theta_{j'})\Big) \geq q\right]. \tag{C.8}$$

Equation (C.8) holds if and only if

$$q \leq \frac{1}{\delta(\theta_{j'}^{[1]})}\Big(\delta(\theta_j^{[1]})\ p + \gamma(\theta_j) - \gamma(\theta_{j'})\Big) \qquad \forall\ q \in Q_l(j, j', p) \tag{C.9}$$

and

$$q \geq \frac{1}{\delta(\theta_{j'}^{[1]})}\Big(\delta(\theta_j^{[1]})\ p + \gamma(\theta_j) - \gamma(\theta_{j'})\Big) \qquad \forall\ q \in Q_u(j, j', p), \tag{C.10}$$

with equations (C.9) and (C.10) holding if and only if

$$q_{l,(j,j')}(p; i) \leq \frac{1}{\delta(\theta_{j'}^{[1]})}\Big(\delta(\theta_j^{[1]})\ p + \gamma(\theta_j) - \gamma(\theta_{j'})\Big) \tag{C.11}$$

and

$$q_{u,(j,j')}(p; i) \geq \frac{1}{\delta(\theta_{j'}^{[1]})}\Big(\delta(\theta_j^{[1]})\ p + \gamma(\theta_j) - \gamma(\theta_{j'})\Big). \tag{C.12}$$

It follows that if $\delta(\theta_{j'}^{[1]}) \neq 0$, then equation (C.5) holds if and only if condition (C.2) holds.

Case 2: Suppose $\delta(\theta_{j'}^{[1]}) = 0$. Then we can rewrite equation (C.5) as

$$D_{j,j'}(p,q;i) = \mathbb{1}\left[\delta(\theta_j^{[1]})\ p + \gamma(\theta_j) - \gamma(\theta_{j'}) \geq 0\right]. \tag{C.13}$$

Using equations (C.6), (C.7), (C.13), and the definitions of supremum and infimum of an empty set,

$$\delta(\theta_j^{[1]})\ p + \gamma(\theta_j) - \gamma(\theta_{j'}) \geq 0 \Leftrightarrow D_{j,j'}(p,q;i) = 1\ \forall\ q \Leftrightarrow Q_u(j,j',p) = \emptyset \Leftrightarrow q_{u,(j,j')}(p;i) = \infty,$$

and

$$\delta(\theta_j^{[1]})\ p + \gamma(\theta_j) - \gamma(\theta_{ij'}) < 0 \Leftrightarrow D_{j,j'}(p,q;i) = 0\ \forall\ q \Leftrightarrow Q_l(j,j',p) = \emptyset \Leftrightarrow q_{l,(j,j')}(p;i) = -\infty.$$

It follows that if $\delta(\theta_{j'}^{[1]}) = 0$, then equation (C.5) holds if and only if either condition (C.3) or condition (C.4) holds.

The cases are exhaustive, which completes the proof. □

We now prove Theorem C.1.

Proof of Theorem C.1. Because θ_i satisfies Assumption 1, $D_{j,j'}(p,q;i) = \mathbb{1}\left[V_j(p;\theta_{ij}) \geq V_{j'}(q;\theta_{ij'})\right]$. Then by applying Lemma C.2 to θ_i and inspecting the definitions given in the statement of Theorem C.1, $\theta_i \in \Theta^{[a]}_{i,(j,j',p)} \cup \Theta^{[b]}_{i,(j,j',p)} \cup \Theta^{[c]}_{i,(j,j',p)}$ for any $(j,j') \in \mathcal{S}'$, $p \in P_{j,j'}$. Since $\theta_i \in \tilde{\Theta}_i$ from Assumption 1, we conclude that $\theta_i \in \Theta_i^\star(\mathcal{S}')$.

We now show that $\Theta_i^\star(\mathcal{S}) = \Theta_i^\star$, where the former set is the proposed set of the theorem as defined by (C.1) and the latter set is the sharp identified set as defined in Definition (5). This follows immediately from comparing the definition of these sets and applying Lemma C.2 to every candidate θ for all $(j,j') \in \mathcal{S}, (p,q) \in \mathbb{R}^2$ such that $(j,j',p,q) \in \mathcal{V}$.

□

Appendix D Identification analysis under the NV design

In this appendix, we revisit the experimental design of Niederle and Vesterlund (2007). We show in Subsection D.1 that the main assertion of NV's conclusions only follows under strong assumptions on individual preferences. In Subsection D.2 we prove the claim made in Remark 4.8 that the sharp identified sets for δ_{ij}, γ_{ij}, and the generalizations of the slope and intercept parameters are unbounded or uninformative under their design if the researcher only imposes Assumption 1.

NV elicit two choices in their experiment: a choice between past tournament (pt) at base-payoff \$2 and past piece rate (pr) at base-payoff \$0.5 applied to the same past performance, and between future tournament (ft) and future piece rate (fr) at the same base-payoffs as for the past choice. Thus, the NV choice experimental design is $\mathcal{V}_{NV} \equiv \{(pt,pr,2,0.5),(ft,fr,2,0.5)\}$. In addition to eliciting past performance $S^*_{i,p} \equiv S^*_{i,(pt)} = S^*_{i,(pr)}$ and gender G_i, the NV design additionally elicits past tournament rank guess $R_{i,p} \in \{1,2,3,4\}$, where rank guess denotes the individual's perceived rank relative to the three individuals they are competing against. The NV experimental design thus corresponds to the choice experimental design $\mathcal{V}_{NV} \equiv \{(pt,pr,2,0.5),(ft,fr,2,0.5)\}$ and associated individual-level observations $(D_{i,\mathcal{V}_{NV}}, X_{i,NV})$, where $D_{i,\mathcal{V}_{NV}} = (D_{i,p}, D_{i,f})$ are indicator variables for choosing tournament over piece rate for past and future compensation schemes, and where $X_{i,NV} = (X_{i1,NV}, X_{i2,NV})$ with

$$X_{i1,NV} = (S^*_{i,(pt)}, G_i) \quad , \quad X_{i2,NV} = R_{i,p}. \tag{D.1}$$

To relate individuals' choices and covariates to beliefs and preferences, we suppose throughout that all individuals i satisfy Assumption 1 with individual-level observation $(D_{i,\mathcal{V}_{NV}}, X_{i,NV})$.

D.1 Implicit restrictions in NV's analysis

The NV design attributes the gender gap in the propensity to enter a future tournament after conditioning on past tournament choice, past performance, and past rank guess, to a gender gap in cost of entering a tournament task (relative to the cost of performing a piece-rate task). The NV assertion is that

$$\begin{aligned} & \Pr\left[D_{i,f} = 1 \middle| D_{i,p} = t, S^*_{i,p} = s, R_{i,p} = r, G_i = \text{male}\right] \\ > \; & \Pr\left[D_{i,f} = 1 \middle| D_{i,p} = t, S^*_{i,p} = s, R_{i,p} = r, G_i = \text{female}\right] \end{aligned} \tag{D.2}$$

implies that men have a higher preference than women for entering a future tournament instead of a piece-rate compensation scheme. Observed past and future choices relate to beliefs and preferences via $D_{i,p} = D_p(\theta_i)$ and $D_{i,f} = D_f(\theta_i)$, where

$$D_p(\theta_i) \equiv \mathbb{1}\left[0.5\left(4\pi_{i,pt}S^*_{i,p} - S^*_{i,p}\right) + \underbrace{\left(\pi_{i,pt}\eta_{i,pt}(1) + (1-\pi_{i,pt})\eta_{i,pt}(0)\right)}_{\equiv \psi_{i,pt}} \geq 0\right], \tag{D.3}$$

and

$$D_f(\theta_i) \equiv \mathbb{1}\left[0.5\left(4\pi_{i,ft}\mu_{i,ft} - \mu_{i,fr}\right) + \left(\underbrace{\pi_{i,ft}\eta_{i,ft}(1) + (1-\pi_{i,ft})\eta_{i,ft}(0) + c_{i,ft}}_{\equiv \psi_{i,ft}}\right) - c_{i,fr} \geq 0)\right]. \tag{D.4}$$

Niederle and Vesterlund (2007) do not provide a formal definition of what they mean by the preference of entering a future tournament. Two candidate parameters are $(\psi_{i,ft} + c_{i,ft}) - c_{i,fr}$, the difference between the cost of entering a future tournament versus a future piece rate, and $c_{i,ft} - c_{i,fr}$, the difference between the cost of performing under a future tournament versus a future piece-rate compensation scheme.[1] For either candidate parameter, a minimum requirement for (D.2) to imply that men have higher preferences for entering future tournaments is that (D.2) implies that the distribution of the candidate parameter for men is not stochastically dominated by the distribution of the candidate parameter for women.

Without further restrictions, (D.2) does not imply this minimum requirement. To illustrate ideas, consider the special case that $\eta_{i,ft}(w) = \eta_{i,pt}(w) = 0$ for $w = 0, 1$ and all i, so that the candidate parameters coincide (the analysis in the general case will require weakly stronger assumptions than those that will be provided). Furthermore, consider the case where we condition on $D_{i,p} = 1$ in equation (D.2) (the case where $D_{i,p} = 0$ follows analogously). Then

$$\begin{aligned} & \Pr\left[D_{i,f} = 1 \middle| D_{i,p} = 1, S^*_{i,p} = s, R_{i,p} = r, G_i = g\right] \\ = \; & \Pr\left[0.5\left(4\pi_{i,ft}\mu_{i,ft} - \mu_{i,fr}\right) + c_{i,ft} - c_{i,fr} \geq 0 \;\middle|\; \pi_{i,pt} \geq \frac{1}{4}, S^*_{i,p} = s, R_{i,p} = r, G_i = g\right]. \end{aligned} \tag{D.5}$$

[1] As our upcoming analysis will make clear, because Niederle and Vesterlund (2007) elicit choices between tournament and piece rate, identification of tournament preferences separately from piece-rate preferences will require additional restrictions beyond those imposed.

The conditioning set relates to the individual's own past performance, beliefs and preferences, and is not directly related to future beliefs or preferences. Thus, it could be, for example, that men tend to have a lower value of $c_{i,ft} - c_{i,fr}$ than women, yet tend to be more overconfident about future performance relative to past performance so that $0.5\left(4\pi_{i,ft}\mu_{i,ft} - \mu_{i,fr}\right)$ tends to be larger for men than women, causing (D.2) to hold despite men having lower preferences than women for entering future tournaments.

As discussed in Section 2, NV appear to (implicitly) discipline this possibility by imposing the restriction that $\pi_i \equiv \pi_{i,ft} = \pi_{i,pt}$ for all i. Assume further that $\mu_{i,ft} = \mu_{i,fr} = S^*_{i,p}$ for all i. These are restrictive assumptions, as they not only rule out differences in beliefs between past and future probabilities of winning, but they also require that both future tournament and piece-rate expected performances equal the realized past tournament performance. Then (D.5) can be written as

$$\Pr\left[0.5s\left(4\pi_i - 1\right) + c_{i,ft} - c_{i,fr} \geq 0 \;\middle|\; \pi_i \geq \frac{1}{4}, S^*_{i,p} = s, R_{i,p} = r, G_i = g\right]. \tag{D.6}$$

Even under these restrictive assumptions, it may be that there is heterogeneity in the subjective probability of winning (π_i) across genders conditional on $\pi_i \geq \frac{1}{4}$, past performance, and past rank guess, so that men tend to have—conditional on these controls—a higher perceived probability of winning relative to women and thus (D.2) holds despite men tending to have a lower value of $c_{i,ft} - c_{i,fr}$.

To proceed, we thus further suppose there exists $\bar{\pi}_{s,r}$ such that $\Pr[\pi_i = \bar{\pi}_{s,r} | \pi_i \geq \frac{1}{4}, S^*_{i,p} = s, R_{i,p} = r] = 1$, so that conditional on these controls, π_i (and thus both $\pi_{i,ft}$ and $\pi_{i,pt}$) is degenerate. This is a restrictive assumption as it implies that, conditional on past score and choosing the tournament compensation scheme in the past, everyone with the same rank guess has the same subjective probability of winning a future tournament.[2]

Let $\bar{\alpha}_{s,r} \equiv -0.5s\left(4\bar{\pi}_{s,r} - 1\right)$. Under these assumptions, (D.6) equals

$$\Pr\left[c_{i,ft} - c_{i,fr} \geq \bar{\alpha}_{s,r} \;\middle|\; \bar{\pi}_{s,r} \geq \frac{1}{4}, S^*_{i,p} = s, R_{i,p} = r, G_i = g\right], \tag{D.7}$$

so that (D.2) implies that the conditional probability that $c_{i,ft} - c_{i,fr}$ exceeds $\bar{\alpha}_{s,r}$ is higher for men than for women, and thus the distribution of $c_{i,ft} - c_{i,fr}$ for men is not stochastically dominated by that for women.

Even under these restrictive assumptions and after imposing that $\eta_{i,ft}(w) = \eta_{i,pt}(w) = 0$ for $w = 0, 1$, this result only holds for a specific $\bar{\alpha}_{s,r}$. We still have no guarantee that the distribution of the value of entering a future tournament relative to piece rate (using either of the two candidate parameter definitions) for men actually stochastically dominates that of women. We cannot think of any reasonable alternative set of assumptions that would yield the conclusions of Niederle and Vesterlund (2007). We conclude that the central assertion of Niederle and Vesterlund (2007), at a minimum, relies on unrealistic assumptions about individual preferences and beliefs and how these preferences and beliefs relate across individuals.

D.2 Statement and proof of Remark 4.8

We formally state and prove the results of Remark 4.8.

[2]Without such an assumption, both an individual who believes they have a 99% chance of winning and an individual who believes they have a 28% chance of winning (and a 24% chance of respectively getting 2nd, 3rd, and 4th) would choose a rank guess of 1.

Theorem D.1. *Given $\mathcal{V}_{NV}$, suppose individual i satisfies Assumption 1. Then*

1. *For all $j \in \mathcal{J} \setminus \{f, pr\}$, the sharp identified set for δ_{ij} is uninformative and the sharp identified set for γ_{ij} is unbounded.*
2. *For any (j, j') where either j or j' is in $\mathcal{J} \setminus \{f, pr\}$, the sharp identified set for $\frac{\delta_{ij}}{\delta_{ij'}}$ is uninformative and the sharp identified set for $\frac{\gamma_{ij}-\gamma_{ij'}}{\delta_{ij'}}$ is unbounded.*

Proof. Proof of Result 1.

We only consider $j \in \{pt, ft, fr\}$ because bounds for δ and γ for all other schemes in $\mathcal{J} \setminus \{f, pr\}$ are trivially uninformative.

Let $\mathcal{S}_{NV} = \{(j, j') \mid \exists\, (p, q) \text{ s.t. } (j, j', p, q) \in \mathcal{V}_{NV}\} = \{(pt, pr), (ft, fr)\}$. For any given $(j, j') \in \mathcal{S}_{NV}$ there only exists one $p \in P_{j,j'}$, namely $p = 2$. Also note that there is only one q for each given $(j, j') \in \mathcal{S}_{NV}$, $p \in P_{j,j'}$ such that $(j, j', p, q) \in \mathcal{V}_{NV}$, namely $q = 0.5$.

Following the results of Online Appendix C, the sharp identified sets for δ_{ij} and γ_{ij} are the $(j, 1)$th and $(j, 2)$th projections, respectively, of $\bar{\beta}(\Theta_i^{\star}(\mathcal{S}_{NV}))$. By Corollary C.1.1, $\bar{\beta}(\Theta_i^{\star}(\mathcal{S}_{NV})) = \mathcal{B}_i(\mathcal{S}_{NV}) \cap \bar{\beta}(\tilde{\Theta}_i)$.

By inspection of $\mathcal{B}_i(\mathcal{S}_{NV})$ and $\tilde{\Theta}_i$, the sharp identified set for δ_{ij} for any $j \in \{pt, ft, fr\}$ is equal to A_{ij} as defined in (28). Thus, using the observation that there is only one base-payoff for each scheme, the sharp identified set for δ_{ij} is uninformative for all $j \in \mathcal{J} \setminus \{f, pr\}$, following the argument in the proof of the necessary condition of Remark 4.2.

We now consider sharp identified sets for γ_{ij}. Because there is only one q for each given $(j, j') \in \mathcal{S}_{NV}$, $p \in P_{j,j'}$ such that $(j, j', p, q) \in \mathcal{V}_{NV}$, namely $q = 0.5$, either $q_{l,(j,j')}(p; i) = -\infty$ and $q_{u,(j,j')}(p; i) = 0.5$, or $q_{l,(j,j')}(p; i) = 0.5$ and $q_{u,(j,j')}(p; i) = \infty$. Then by inspection of $\mathcal{B}_i(\mathcal{S}_{NV})$ and $\tilde{\Theta}_i$, it is evident that for any $j \in \{pt, ft, fr\}$ it is possible to construct a candidate $\theta = \theta_i$ except for γ_j which can be unbounded in one direction above or below γ_{ij} (the direction depends on whether $q_{l,(j,j')}(p; i) = -\infty$ or $q_{u,(j,j')}(p; i) = \infty$ and what j is). This candidate θ satisfies the constraints of $\mathcal{B}_i(\mathcal{S}_{NV})$ and $\tilde{\Theta}_i$, meaning that the sharp identified set for γ_{ij} must be unbounded.

Proof of Result 2.

We only consider $(j, j') \in \mathcal{S}_{NV} = \{(pt, pr), (ft, fr)\}$ because bounds for the expressions considered in this result for all other (j, j') with j or j' in $\mathcal{J} \setminus \{f, pr\}$ are trivially unbounded/uninformative.

For any $(j, j') \in \mathcal{S}_{NV}$, the restrictions of $\tilde{\Theta}$ are such that for any candidate $\theta \in \tilde{\Theta}$, $\gamma_j, \gamma_{j'}$ can take on any value in $(-\infty, \infty)$. Then it is possible to construct a candidate $\theta \in \tilde{\Theta}$ where $\frac{\delta_j}{\delta_{j'}} = x$ for any $x \in [0, \infty)$, because either $q_{l,(j,j')}(p; i) = -\infty$ or $q_{u,(j,j')}(p; i) = \infty$, so we can accordingly adjust γ_j or $\gamma_{j'}$ such that restrictions from $\mathcal{B}_i(\mathcal{S}_{NV})$ still hold. Therefore the sharp identified set for $\frac{\delta_{ij}}{\delta_{ij'}}$ contains $[0, \infty)$ and so is uninformative.

For any $(j, j') \in \mathcal{S}_{NV}$, we noted that it is always the case that either $q_{l,(j,j')}(p; i) = -\infty$ or $q_{u,(j,j')}(p; i) = -\infty$. Then we can construct a candidate $\theta = \theta_i$ except for γ_j, which will be unbounded in one direction above or below γ_{ij} depending on if $q_{l,(j,j')}(p; i) = -\infty$ or $q_{u,(j,j')}(p; i) = \infty$, such that this candidate θ satisfies the restrictions of $\mathcal{B}_i(\mathcal{S}_{NV})$. Because θ also satisfies the restrictions of $\tilde{\Theta}$, the sharp identified set for $\frac{\gamma_{ij}-\gamma_{ij'}}{\delta_{ij'}}$ is unbounded.

□

Appendix E Investigating validity of model

Our model imposes that beliefs and preferences are base-payoff invariant and that risk preferences do not influence valuations of compensation schemes. In Subsection E.1, we test if beliefs are base-payoff invariant. In Subsection E.2, we test whether

Table E.1: Regression of rank guess on base-payoff

	Dependent variable:
	Rank guess
Female	0.081
	(0.141)
Second addition task	−0.060
	(0.076)
Third addition task	−0.094
	(0.084)
Base-payoff	−0.021
	(0.053)
Score	-0.158^{***}
	(0.021)
(Intercept)	3.323^{***}
	(0.225)
Observations	441
Residual Std. Error	0.964 (df = 435)

Notes: *p<0.1; **p<0.05; ***p<0.01. This table presents results from a regression of rank guess on base-payoff and other controls, with standard errors reported in parentheses. Standard errors are clustered at the individual level. Sample is restricted to the baseline sample. The coefficient on base-payoff has a p-value of 0.69.

risk preferences influence valuations of compensation schemes, and also examine whether there is a gender difference in risk preferences. In Subsection E.3, we examine the testable restriction of risk neutrality described in Remark 4.3.

E.1 Beliefs and base-payoffs

Online Appendix Table E.1 presents coefficients from a regression of past rank guess (a proxy for beliefs) on base-payoff, task performance, the timing of task, and gender. The coefficient on base-payoff is small and insignificant, suggesting beliefs are base-payoff invariant.

E.2 The role of risk preferences

We elicit risk preferences following the Holt and Laury (2002) design (HL design). In the HL design, participants are presented with a menu of ten different choices between paired lotteries, one of which has payoffs that are more variable than the other (and thus riskier). Each decision presents a choice between lotteries with an increasingly negative payoff difference. We implement the high payoff version of their method in our experiment. We consider two measures of risk preferences. First, following Holt and Laury (2002), we consider the number of times the participant chooses the "safe" option (denoted number of safe choices) as a measure of relative risk aversion. Second, we use the mapping between number of safe choices and relative risk aversion to set-identify relative risk aversion (see Table 3 of Holt and Laury (2002)).

Table E.2: Regressions of valuation on RRA

	Dependent variable:
	Midpoint of payoff indifference set
RRA safe choices, FT Future 3.2	0.008
	(0.180)
RRA safe choices, FT Future 6.4	−0.023
	(0.230)
RRA safe choices, FT Future 9.6	0.145
	(0.370)
RRA safe choices, FT Past 3.2	−0.074
	(0.143)
RRA safe choices FT Past 6.4	−0.151
	(0.240)
RRA safe choices, FT Past 9.6	−0.314
	(0.441)
Observations	1,604
R^2	0.465
Adjusted R^2	0.457
Residual Std. Error	9.248 (df = 1580)

Notes: *p<0.1; **p<0.05; ***p<0.01. This table presents results from regressing, for each past or future tournament and base-payoff, the midpoints of payoff indifference sets on the number of safe choices, gender, and performance. We only display coefficients for the estimated effect of number of safe choices on midpoints. When the payoff indifference set is bounded, the midpoint is well defined. When the payoff indifference set is unbounded below (above), we instead use the upper (lower) bound of the payoff indifference set. Standard errors are clustered at the individual level and reported in parentheses. Sample is restricted to the baseline sample. We fail to reject a joint test of all coefficients being zero ($p = 0.98$).

We first examine whether risk preferences influence valuations for past and future tournaments by regressing, for each past or future tournament and base-payoff, the midpoints of payoff indifference sets on the number of safe choices, gender, and performance. Online Appendix Table E.2 presents the coefficient on the number of safe choices for each such regression. The coefficients are all small and insignificant, and we fail to reject a joint test of all coefficients being zero ($p = 0.98$). These results support our assumption that risk preferences do not influence valuations of compensation schemes.

We next examine relative risk aversion and how it differs by gender. Because the HL design elicits risk aversion via an MPL, we set-identify relative risk aversion and can perform inference on group-level means of risk preference following our methods for estimation and inference detailed in Example B.1.

Online Appendix Table E.3 reports bounds on mean relative risk aversion by gender and for the gender difference in mean relative risk aversion. We restrict our analysis to individuals with bounded identified sets, and thus exclude individuals who always choose the safer option or always choose the riskier option. We find that both genders are, on average, slightly risk averse, but we fail to find a significant difference in mean relative risk aversion by gender.

Table E.3: Difference in risk preference

Male	Female	Male - Female
[0.209,0.510]***	[0.395,0.704]***	[-0.495,0.115]
(0.101,0.612)	(0.302,0.799)	(-0.638,0.253)

Notes: *p<0.1; **p<0.05; ***p<0.01. This table presents bounds (in brackets) and 95% CIs (in parentheses) on mean RRA by gender, with the gender difference in bounds on RRA in the last column. Sample is restricted to the baseline sample, and we further drop individuals with unbounded RRA. We test whether RRA and the gender difference in RRA is statistically different from zero.

E.3 Testing linearity

Finally, we examine the testable restriction of risk neutrality described in Remark 4.3. Specifically, if participants are risk-neutral, the linear programs solved as in Remark 4.4 should be feasible. Infeasible programs are a rejection of the testable restriction. Online Appendix Table E.4 presents the share of infeasible linear programs by gender and pair of schemes. We see that only a small share of programs are infeasible, and differences in the share of infeasible sets by gender are small.

Table E.4: Properties of linear programs

MPL type	Gender	Informative	Uninformative	Infeasible
Past Tournament - Fixed Pay (avg)	male	0.90	0.08	0.00
Past Tournament - Fixed Pay (avg)	female	0.98	0.01	0.00
Future Tournament - Fixed Pay	male	0.78	0.11	0.11
Future Tournament - Fixed Pay	female	0.89	0.01	0.10
Future Lumpsum Tournament - Fixed Pay	male	0.73	0.08	0.19
Future Lumpsum Tournament - Fixed Pay	female	0.86	0.02	0.12

Notes: This table presents the share of linear programs that are informative, uninformative, and infeasible by MPL type and gender. MPLs take the form of 'scheme X – scheme Y', where scheme X is fixed at the listed base-payoff and scheme Y varies in base-payoff. MPLs with '(avg)' denote taking, for each individual, the mean of multiple MPLs at the given base-payoff, as is the case for past tournament since individuals perform three past tasks and complete MPLs at the listed base-payoffs for each of these past performances. Sample is restricted to the baseline sample. Shares for each gender and MPL type may not sum to 1 due to rounding.

Appendix F Investigating consistency between elicitation methods

The NV design elicits Take-It-Or-Leave-It (TIOLI) choices between tournament and piece-rate schemes, whereas our analysis uses MPLs that elicit choices between these schemes and fixed pay. We exploit that our experimental design includes both elicitation methods to examine consistency between them.

This appendix describes the consistency checks we perform. In 90% of the cases, TIOLI and MPL-elicited choices between tournament and piece-rate schemes are consistent with each other. In 84% of cases, MPL-elicited choices between tournament and piece-rate schemes are consistent with MPL-elicited choices between these schemes and fixed pay. These shares are similar by gender. Coupled with our near-exact replication of the main result of Niederle and Vesterlund (2007) using their methods on our data, these results suggest that any differences in our conclusions from Niederle and Vesterlund (2007) follow from our alternative methodology and not from our differing experimental samples or choice of elicitation methods.

In Subsection F.1, we examine consistency between TIOLI choices and MPLs that elicit choices between tournament and piece-rate schemes. In Subsection F.2, we examine consistency between MPLs that elicit choices between tournament and piece-rate schemes and MPLs that elicit choices between these schemes and fixed pay.

F.1 Consistency between oneshots and MPLs

Individuals complete MPLs between past tournament and fixed pay. Individuals also complete MPLs between future tournament and future piece rate. Because past piece rate is equivalent to a fixed pay scheme scaled by the past performance, we can think of an MPL between past tournament and fixed pay as equivalent to an MPL between past tournament and an appropriately scaled past piece rate. Separately, individuals complete TIOLIs between past tournament and past piece rate and between future tournament and future piece rate. Both MPLs and TIOLIs imply payoff indifference sets (the latter of which will always be unbounded in one direction).

To verify whether individuals are consistent between MPLs and TIOLIs, we check whether the payoff indifference sets intersect nontrivially. We find that 90% of TIOLIs and MPLs are consistent with each other, with that figure equal to 89% for men and 90% for women.

F.2 Consistency between fixed pay and non-fixed pay MPLs

Individuals also complete MPLs between future tournament and future piece rate. Thus we can verify whether individuals are consistent between MPLs between future tournament and future piece rate and MPLs between future tournament and fixed pay.

In particular, consider any piece-rate base-payoff r and tournament base-payoff t. Let $[r_l(t), r_u(t)]$, $[f_l(r), f_u(r)]$, and $[f_l(t), f_u(t)]$ respectively denote the payoff indifference sets for future tournament (in terms of future piece rate), for future piece rate (in terms of fixed pay), and future tournament (in terms of fixed pay). If $r \geq r_u(t)$, then

$$f_u(r) \succcurlyeq r \geq r_u(t) \succcurlyeq f_l(t) \implies f_u(r) \geq f_l(t). \tag{F.1}$$

Similarly, if $r \leq r_l(t)$, it must be that $f_l(r) \leq f_u(t)$. We can thus check whether this holds for every (r, t) pair for which there exists a MPL between future piece rate at base-payoff r and fixed pay, a MPL between future tournament at base-payoff t and future piece rate, and a MPL between future tournament at base-payoff t and fixed pay in the experiment. We find that the share of cases for which this consistency check holds is 85%. That figure is 88% for men and 82% for women.

Appendix G Explicit definitions of considered parameters

Online Appendix Table G.1 explicitly defines the individual-level identified sets for all parameters (apart from considered differences in these parameters) considered in Table 2, Table 3, Online Appendix Table A.6, and Online Appendix Table A.7. Individual-level identified sets for considered differences in the parameters are constructed following Examples A.2 and A.3 and are a function of the presented identified sets for the individuals parameters.

Online Appendix Table G.2 explicitly defines the individual-level identified sets for all differences between pairs of variables X and Y (denoted $X - Y$) mentioned in Table 4 and Table 5. Individual identified sets for $\mathbb{1}\{X \neq Y\}$ and $\mathbb{1}\{X > Y\}$ are then constructed following Example A.2. Specifically, if we let $[\tau_{i,l}, \tau_{i,u}]$ denote the individual identified set on $X - Y$, the individual identified set for $\mathbb{1}\{X \neq Y\}$ is $\{1\}$ if $[\tau_{i,l}, \tau_{i,u}] \subseteq \mathbb{R} \setminus \{0\}$, $\{0\}$ if $[\tau_{i,l}, \tau_{i,u}] \subseteq \{0\}$, and $\{0, 1\}$ otherwise.

Table G.1: Individual bounds on beliefs and non-monetary preferences

Parameter	Description	Individual bounds (or point)
Panel A: beliefs		
	Objective probability of winning	$\frac{1}{n}\sum_{\ell=1}^{n}\pi^*(S^*_{i,(pt,\ell)})$
$\pi_{i,pt}$	Past subjective probability of winning	$[\frac{1}{n}\sum_{\ell=1}^{n}\delta_{i,(pt,\ell),l}/S^*_{i,(pt,\ell)}, \frac{1}{n}\sum_{\ell=1}^{n}\delta_{i,(pt,\ell),u}/S^*_{i,(pt,\ell)}]$
$\pi_{i,fl}$	Future subjective probability of winning	$[\delta_{i,fl,l}, \delta_{i,fl,u}]$
Panel B: non-monetary preferences		
$\psi_{i,pt}$	Past tournament non-monetary preference	$[\frac{1}{n}\sum_{\ell=1}^{n}\gamma_{i,(pt,\ell),l}, \frac{1}{n}\sum_{\ell=1}^{n}\gamma_{i,(pt,\ell),u}]$
$\psi_{i,ft}+c_{i,ft}$	Future tournament non-monetary preference	$[\gamma_{i,ft,l}, \gamma_{i,ft,u}]$
Panel C: expected monetary value		
	Objective tournament expected monetary value	$\frac{1}{n}\sum_{\ell=1}^{n}\pi^*(S^*_{i,(pt,\ell)})\cdot S^*_{i,(pt,\ell)}$
$\pi_{i,pt}\mu_{i,pt}$	Past subjective tournament expected monetary value	$[\frac{1}{n}\sum_{\ell=1}^{n}\delta_{i,pt,l}, \frac{1}{n}\sum_{\ell=1}^{n}\delta_{i,pt,u}]$
$\pi_{i,ft}\mu_{i,ft}$	Future subjective tournament expected monetary value	$[\delta_{i,ft,l}, \delta_{i,ft,u}]$

Notes: This table defines individual identified sets for all individual belief and preference parameters mentioned in Table 2, Table 3, Online Appendix Table A.6, and Online Appendix Table A.7, except for differences between parameters. Point values for objective probability of winning are calculated as described in Subsection 6.2. In particular, given any individual's realized ℓ-th past tournament score $S^*_{i,(pt,\ell)}$, let $\pi^*(S^*_{i,(pt,\ell)})$ denote the cube of the sample CDF of all past performances evaluated at $S^*_{i,(pt,\ell)}$. Then i's objective probability of winning is the average of $\pi^*(S^*_{i,(pt,\ell)})$ over all past tournaments, and i's objective tournament expected monetary value is the average of $\pi^*(S^*_{i,(pt,\ell)})\cdot S^*_{i,(pt,\ell)}$ over all past tournaments. In our experimental design we elicit choices for multiple past tournament schemes, and index the n past tournament schemes as (pt,k) for $k=1,\ldots,n$. All other notation follows that of Section 3 and Section 4. See Subsection 6.2 for further details on construction of the bounds.

Table G.2: Individual bounds on differences in beliefs and preferences

Variable X	Variable Y	Individual bounds on $X-Y$
Past subjective probability of winning	Objective probability of winning	$[\pi_{i,pt,l}-\frac{1}{n}\sum_{\ell=1}^{n}\pi^*(S^*_{i,(pt,\ell)}), \pi_{i,pt,u}-\frac{1}{n}\sum_{\ell=1}^{n}\pi^*(S^*_{i,(pt,\ell)})]$
Future subjective probability of winning	Objective probability of winning	$[\pi_{i,fl,l}-\frac{1}{n}\sum_{\ell=1}^{n}\pi^*(S^*_{i,(pt,\ell)}), \pi_{i,fl,u}-\frac{1}{n}\sum_{\ell=1}^{n}\pi^*(S^*_{i,(pt,\ell)})]$
Future subjective probability of winning	Past subjective probability of winning	$[\pi_{i,fl,l}-\pi_{i,pt,u}, \pi_{i,fl,u}-\pi_{i,pt,l}]$

Notes: This table defines individual identified sets for all differences between pairs of variables X and Y mentioned in Table 4 and Table 5. For any parameter τ_i^* listed in Online Appendix Table G.1, $[\tau_{i,l}, \tau_{i,u}]$ denotes the individual identified set on τ_i^* detailed in Online Appendix Table G.1. Other notation follows that of Section 3, Section 4, and table notes for Online Appendix Table G.1.

Appendix H Outline of the experiment

The experiment was conducted between January and March 2020 at the Behavioral Research Lab (BRL) at Yale University. Participants were recruited by the BRL using standard procedures. We recruited 176 participants in total, of which 59% were female. (The total BRL participant pool is about 62% female). We conducted 19 sessions, with an average number of nine participants per session. Sessions would only be conducted if the female share of participants was roughly 60%. The average gender composition per session was 57%. Participants received a $5 show-up fee and a $7 completion fee. The average payment was $30. Participants were told up front that there were many parts in the experiment and that a randomly selected part (or a selected row if it was an MPL) would be implemented as payment.

H.1 Addition tasks and base-payoff

In our experiment, each participant completed a series of addition tasks. In an addition task, participants complete a 3-minute, two-digit addition problem under given compensation schemes. Online Appendix Figure H.1 shows an example of an addition task.

There are six types of compensation schemes that could be applied to addition tasks. The first four compensation schemes (past and future piece rate, past and future tournament) are frequently used in the gender and competitiveness literature following the Niederle and Vesterlund (2007) design.[3] To identify a richer set of parameters, we add two new compensation schemes: fixed pay and future lumpsum tournament. The six compensation schemes are defined as follows:

Past/Future Piece Rate: Under a past or future piece-rate scheme, payment is a base-payoff multiplied by the number of questions a participant solves correctly on a 3-minute addition task. Payment does not decrease if an incorrect answer to a problem is provided.

Past/Future Tournament: Under a past or future tournament scheme, payment depends on participants' performance relative to that of a group of other participants. In this experiment, all tournaments consisted of four people randomly chosen in the room, and the group composition was fixed at the start of the experiment. If a participant were to solve the most problems in her group, she would receive the tournament price per correct problem; otherwise, she would receive no payment. When there were ties for the highest score, both winners would receive the tournament price per correct problem.

Fixed Pay: Under the fixed pay scheme, payment is disbursed according to a fixed price and does not depend on participants' performance in the addition tasks. For example, under fixed pay of \$1, a participant will always receive \$1 no matter how many questions she correctly computes in an addition task.

Future Lumpsum Tournament: The future lumpsum tournament scheme is similar to the future tournament compensation scheme. However, under the future lumpsum tournament, if a participant wins a tournament as described above, she receives a lumpsum payment; otherwise, she receives \$0. The amount of lumpsum payment does not depend on the number of questions she solves correctly during the addition task.

In our experiment, all participants were expected to perform at least six addition tasks under various *base-payoffs*. A base-payoff is the piece-rate or tournament payment per correct question. In this experiment we used three base-payoffs for the piece-rate scheme, at \$0.8, \$1.6, and \$2.4 per correct question. We also used three base-payoffs for the tournament scheme, at \$3.2, \$6.4, and \$9.6 per correct question. We notified participants about these base-payoffs before the start of each relevant addition task. If a row of an MPL applied to a future addition task was selected for payment, that participant performed an extra addition task at the end of the experiment.

H.2 MPL

In the experiment, participants were asked to fill out MPLs that elicited their preference between scheme-payoffs.[4] In the instruction manual and during the experiment we refer to these MPLs as "choice tables" to make the concept easier to

[3] In the original Niederle and Vesterlund (2007) experiment, participants were asked to choose between piece rate at \$0.5 per correct question versus tournament at \$2 per correct question under different task status (i.e. past or future).

[4] Since the compensation schemes can be grouped according to different price levels, we call the groupings "scheme-payoff" in the main manuscript. For example, the piece-rate addition task at \$0.8 per correct question is a scheme-payoff.

understand. Online Appendix Figure H.3(a) presents an example of one such MPL involving a tournament scheme at $3.2 base-payoff and fixed pay. In this example, Option A comprises fixed pay at ascending payoffs, whereas Option B comprises a future tournament at $3.2 per correct question. All MPLs in our experiment had this structure: Option A contained fixed pay with ascending payoffs, whereas Option B contained a constant scheme-payoff.[5] All MPLs in the experiment contained 36 rows. For each row, knowing that their choices will be randomly implemented at the end of the experiment, participants chose whether they preferred to apply Option A or Option B to their relevant performance.

H.3 Experiment flow

The experiment consisted of seven stages, and Online Appendix Figure H.2 presents a summary of the experiment flow. Stage 1 involved practice rounds for addition tasks and MPLs. Stage 2 and stage 3 were addition tasks. Performance in stage 2 was compensated under a piece-rate scheme if this stage was randomly selected for payment, whereas performance in stage 3 was compensated under a tournament scheme if this was selected. In stage 4, participants filled out MPLs regarding their performance in stage 3 (i.e., past tournament performance). In stage 5, participants were asked to decide whether they would like to be compensated under a piece-rate or tournament scheme for their past piece-rate performance in stage 2. This stage was designed to replicate task 4 in the Niederle and Vesterlund (2007) study (NV hereafter). In stage 6, participants filled out MPLs regarding a future addition task. In stage 7, participants were asked to decide whether they would like to be compensated under a piece-rate or tournament scheme for the future addition task. This stage is designed to replicate task 3 in the NV study. Participants learned about their performance at the end of stage 2 and stage 3. They were reminded of their performance before the start of stage 4 and stage 5. Participants were told that if stage 6 or 7 was chosen for payment, they would have to perform another addition task at the end of the experiment.

Stages 2 to 5 and stages 6 to 7 were repeated *three* times. We called each repetition a "period." In each period, participants were presented with one of the three *base-payoffs* as defined above. It should be noted that the piece-rate and tournament base-payoffs appeared in pairs, but the order of appearance was randomized for each participant. Hence, for a particular period, if the chosen piece-rate base-payoff was $2.4 per correct question in stage 2, then the tournament base-payoff would be $9.6 in stage 3. However, in the same period, another participant could be working with a piece-rate base-payoff of $1.6 per correct question and a tournament base-payoff of $6.4 per correct question.

Suppose a participant scored 10 correct questions in both stage 2 and stage 3 in a particular period. If stage 2 of this period were chosen for payment, she would be paid $\$2.4 \times 10 = \$24$. If stage 3 were chosen, she would be paid $\$9.6 \times 10 = \$96$ if nobody in her group scored higher than 10 at the same base payoff in stage 3. It should be noted that her group members' order of base-payoffs could be different. Therefore, the participant could be competing with other members' stage 3 performances from a different period.

Stages 4 through 7 consisted of MPLs and one-shot valuation questions. The structures of stages 4 and 5 were highly similar to those of stages 6 and 7. The main difference was that the MPLs and the one-shot valuation questions in stages 4 and 5 dealt with *past performances*, whereas stages 6 and 7 dealt with *future performances*. In each period of stage 4, participants filled out three MPLs, as shown in Online Appendix Figure H.3. All three MPLs listed tournaments at base-payoffs of $3.2, $6.4, and $9.6 in Option B, as well as varying fixed pay in Option A. Taking the same participant who

[5] In stage 6 of the experiment, we introduced two new MPLs with a slightly different structure. Please see the discussions of experiment flow in Online Appendix H.3 below.

scored 10 in both stages 2 and 3 as an example, stage 4 essentially asked the participant if, knowing that she scored 10 in stage 3, she would like to apply the fixed payoff listed in Option A or tournament base-payoff listed in Option B to her past tournament performance. If a randomly selected row in this stage was chosen for payment and the participant chose fixed pay, she would be paid the indicated fixed amount regardless of her performance. If she chose the tournament, then she would submit her score (10) to compete with other participants' tournament scores at the same base-payoff and be paid accordingly.[6]

During each period of stage 6, participants were asked to fill out five MPLs regarding their future performances, with a different base-payoff for each period. Online Appendix Figures H.4, H.5, and H.6 list all 15 MPLs that appear in stage 6 in three periods. The first three MPLs (panels (a)-(c)) have a familiar structure: Option A comprised fixed pay with ascending payoffs, whereas Option B contains a constant scheme-payoff pair. The scheme-payoff pairs listed in Option B in this stage included piece-rate, tournament, and lumpsum tournament schemes, to be applied to participants' future performances. Stage 6 comprised two additional MPLs that did not use fixed pay as the alternatives (panels (d)-(e)). Instead, these two MPLs asked participants to compare a constant tournament (piece-rate) scheme listed in Option B versus a piece-rate (tournament) scheme at ascending prices listed in Option A. In stage 7, participants were asked to decide whether they would like to be compensated under a piece-rate or tournament scheme for the future addition task. Participants were told that if stage 6 or 7 were chosen for payment, they would need to perform an additional 3-minute addition task at the end of the experiment and be paid accordingly. Before they performed the future addition tasks, they learned the chosen row that would be implemented.

During each period of stages 6 and 7, one of the three pairs of base-payoffs were randomly used. For example, if participants were presented a piece-rate base-payoff of \$2.4 per correct question and tournament base-payoff of \$9.6 per correct question in a particular period, in stage 6 of this period, participants would fill out MPLs as shown in Online Appendix Figure H.6. If one of the first three MPLs was randomly chosen for payment, one row would be randomly picked. If the participant chose fixed pay, she would be paid the indicated amount regardless of her performance at the end of the experiment. If she chose piece-rate, she would be paid \$2.4 per correct question based on her future performance. If she chose the tournament or lumpsum tournament schemes, she would compete with her group members' past tournament performances at the same base-payoff. In other words, she would not compete with those that chose the tournament scheme in this stage but only with her group members' performances in stage 3 at a base-payoff of \$9.6. If an MPL in Online Appendix Figure H.6(d) was chosen for payment, she would also need to perform an extra addition task at the end of the experiment. If the piece-rate scheme was chosen in the randomly chosen row, the participant would be paid according to the indicated piece-rate base-payoff multiplied by her future performance. If the tournament scheme was chosen, she would compete with group members' stage 3 performances at a base-payoff of \$9.6 and be paid accordingly. If the MPL in Online Appendix Figure H.6(e) was chosen for payment and the piece-rate scheme was chosen in the randomly selected row, she would be paid \$2.4 per correct question for her future performance. If the tournament scheme was chosen, the situation becomes slightly tricky, as there would not be that many tournament base-payoffs in stage 3. Therefore, in this case, we compared the future performance with group members' piece-rate performance at \$2.4 in stage 2.

[6]Since participants could receive different scores for stage 3 in different periods, it made sense to have them fill out identical MPLs in each period. However, it was also possible that performances would not change between periods. In that case, stage 4 of the specific period would be skipped.

H.4 Implementation details of MPL

It is important to make sure that participants understand the concept of a MPL and minimize the errors that they make. In this section, we discuss how the MPLs were designed and implemented to achieve these goals.

Iterated MPL As discussed above, each MPL contained 36 rows of scheme-payoff pairs. To reduce the burden of choice for participants, we followed the iterative multiple price list (iMPL) design proposed by Andersen, Harrison, Lau, and Rutström (2006). iMPL allows participants to choose from refined options from within the options last selected. In our setting, we divided the 36 rows in a given MPL into segments of six. We first asked participants to make decisions for rows 1, 7, 13, 19, 25, and 31. (We call this a sub-choice table 1 in the experiment). If a switching point was observed in sub-choice table 1, the five rows immediately above the switching point were displayed. Online Appendix Figure H.7a shows a sub-choice table 1 MPL with the tournament scheme at a base-payoff of \$3.2 in Option B and fixed pay going from \$0 to \$12. Suppose there were a switching point at row 4; the participant would then be prompted with a sub-choice table 2 MPL, as shown in Online Appendix Figure H.7b. The sub-choice table 2 MPL would expand the rows between fixed pay of \$4.8 and \$7.2 so that a more refined switching point could be identified.

Multiple Switchers Our model does not explicitly deal with individuals that are multiple switchers (i.e. those that tend to switch back and forth between options within an MPL). However, multiple switchers comprise a substantial proportion of participants in many field and lab experiments, and according to existing literature, this indicates poor quality of decision making (Yu, Zhang, and Zuo, 2020). If multiple switchers comprise a large portion of participants, this might pose a threat to our structural model. Overall, these individuals represent a rather small portion of our data. In the experiment, if we observed more than two switching points in a stage-1 MPL, we only expanded the five rows immediately before the first switching point. In the empirical analyses, we dropped observations of twenty-five individuals that either left blank or switched multiple times on MPLs that elicited choices between fixed pay and competitive schemes.

No Switching Point If no switching point was observed in a stage-1 MPL and the participant always chose Option B, we expanded the last 5 rows from 32 to 36. Online Appendix Figures H.7c and H.7d show an example of a participant who always chose B in stage 1. To increase the likelihood of observing a switching point, the intervals in 32 to 36 were made wider than those in the previous rows. (All rows before 32 had the same width.) If the participant still always chose Option B in stage-2, then they would be identified as a non-switcher.

If a participant always chose Option A in a stage-1 MPL, there was little we could do to force her to switch (as we can not go into negative payments in Option A), and the stage-2 choice table was skipped with the participant recorded as a non-switcher. By design, the value in row 1 of column A in all choice tables was set as equal to or very close to zero. Choosing all Option A in stage 1 meant the participant was potentially willing to pay out of pocket to remain in the compensation scheme. A more sophisticated experimental design would incorporate this possibility and elicit participants' willingness to pay to stay in a compensation scheme. This can be a direction for future research.

H.5 Other details

In the practice rounds in stage 1, we asked participants to perform a 3-minute piece-rate addition task and a 3-minute tournament addition task, followed by a practice MPL that asked participants to choose between \$0.5 per correct answer and varying fixed pay to be applied to the piece-rate addition task they had just finished. Since participants were notified of

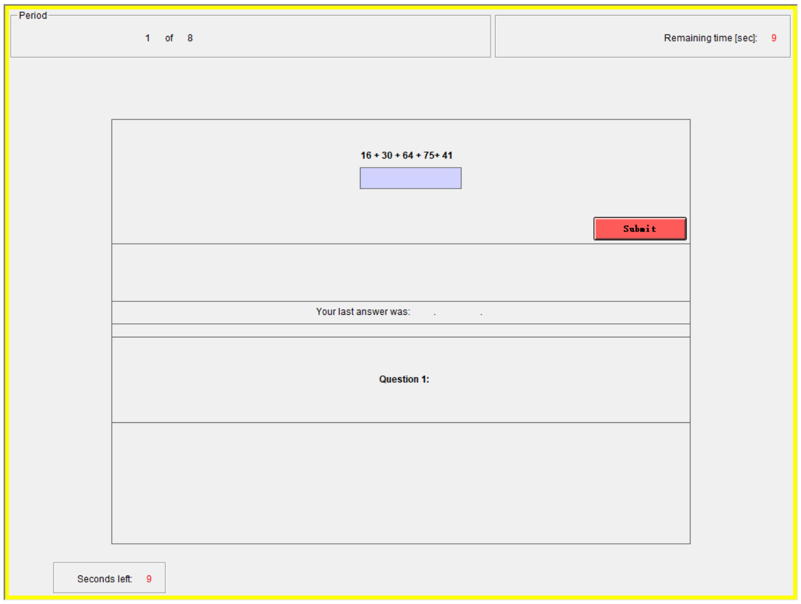


Figure H.1: Addition task

their piece-rate performance, from this MPL, we could infer if the participants truly understood the meaning of these tables.

At the end of the experiment, before the last addition task that some of the participants had to perform, participants were asked to fill out a series of questionnaires. The questionnaires included their rank guesses for the stage 3 performances at all three base-payoffs and their rank guess for future performance if they were selected to perform. Participants were paid \$0.5 for each correct guess. We also collected information on participants' gender, country of origin, major, and GPA.

In our experiment, we closely follow Holt and Laury (2002) and elicit participants' risk preference using two MPLs, each with 10 choices between paired gambles. We use the same gamble pairs as shown in Holt and Laury (2002) Table 1 and a second MPL with all payoffs multiplied by 10.[7] Following the literature, we use the number of safe choices as a control for risk preference in our analyses. The number of safe choices is computed as the number of choices (among the 10 in the same MPL) that are Option A. The higher the number of safe choices made by a participant, the higher their level of risk aversion.

[7]Holt and Laury (2002) used the base case (Table 1 in their paper) and 20x payoff in each experiment to see changes in risk preference from low to high payoff. We use 10x payoff in order to match the range of high payoff in our experiment.

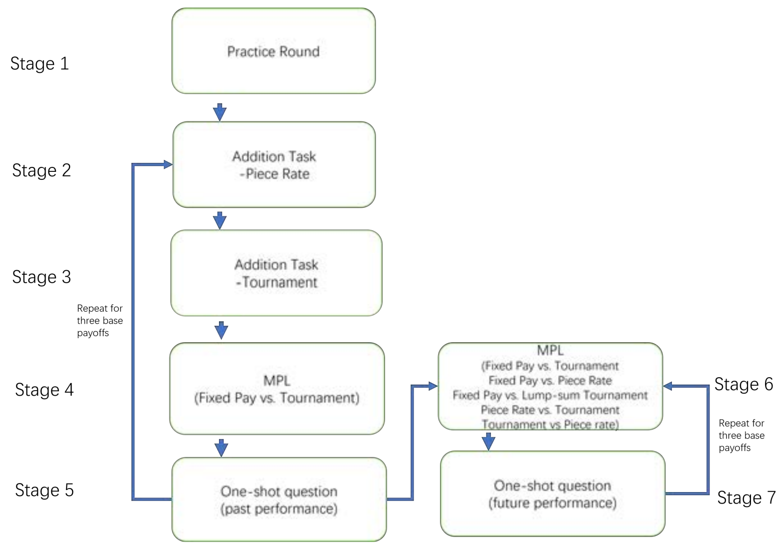


Figure H.2: Experiment flow

Row #	Option A: Fixed Pay	Option B: Tournament
1	0.0	3.2
2	0.4	3.2
3	0.8	3.2
4	1.2	3.2
5	1.6	3.2
6	2.0	3.2
7	2.4	3.2
8	2.8	3.2
9	3.2	3.2
10	3.6	3.2
11	4.0	3.2
12	4.4	3.2
13	4.8	3.2
14	5.2	3.2
15	5.6	3.2
16	6.0	3.2
17	6.4	3.2
18	6.8	3.2
19	7.2	3.2
20	7.6	3.2
21	8.0	3.2
22	8.4	3.2
23	8.8	3.2
24	9.2	3.2
25	9.6	3.2
26	10.0	3.2
27	10.4	3.2
28	10.8	3.2
29	11.2	3.2
30	11.6	3.2
31	12.0	3.2
32	13.6	3.2
33	15.2	3.2
34	16.8	3.2
35	18.4	3.2
36	20.0	3.2

(a) base payoff = 3.2

Row #	Option A: Fixed Pay	Option B: Tournament
1	0	6.4
2	0.8	6.4
3	1.6	6.4
4	2.4	6.4
5	3.2	6.4
6	4.0	6.4
7	4.8	6.4
8	5.6	6.4
9	6.4	6.4
10	7.2	6.4
11	8.0	6.4
12	8.8	6.4
13	9.6	6.4
14	10.4	6.4
15	11.2	6.4
16	12.0	6.4
17	12.8	6.4
18	13.6	6.4
19	14.4	6.4
20	15.2	6.4
21	16.0	6.4
22	16.8	6.4
23	17.6	6.4
24	18.4	6.4
25	19.2	6.4
26	20.0	6.4
27	20.8	6.4
28	21.6	6.4
29	22.4	6.4
30	23.2	6.4
31	24.0	6.4
32	27.2	6.4
33	30.4	6.4
34	33.6	6.4
35	36.8	6.4
36	40.0	6.4

(b) base payoff = 6.4

Row #	Option A: Fixed Pay	Option B: Tournament
1	0	9.6
2	1.2	9.6
3	2.4	9.6
4	3.6	9.6
5	4.8	9.6
6	6.0	9.6
7	7.2	9.6
8	8.4	9.6
9	9.6	9.6
10	10.8	9.6
11	12.0	9.6
12	13.2	9.6
13	14.4	9.6
14	15.6	9.6
15	16.8	9.6
16	18.0	9.6
17	19.2	9.6
18	20.4	9.6
19	21.6	9.6
20	22.8	9.6
21	24.0	9.6
22	25.2	9.6
23	26.4	9.6
24	27.6	9.6
25	28.8	9.6
26	30.0	9.6
27	31.2	9.6
28	32.4	9.6
29	33.6	9.6
30	34.8	9.6
31	36.0	9.6
32	40.8	9.6
33	45.6	9.6
34	50.4	9.6
35	55.2	9.6
36	60.0	9.6

(c) base payoff = 9.6

Figure H.3: MPLs for stage 4

Row #	Option A: Fixed Pay	Option B: Piece Rate
1	0.0	0.8
2	0.4	0.8
3	0.8	0.8
4	1.2	0.8
5	1.6	0.8
6	2.0	0.8
7	2.4	0.8
8	2.8	0.8
9	3.2	0.8
10	3.6	0.8
11	4.0	0.8
12	4.4	0.8
13	4.8	0.8
14	5.2	0.8
15	5.6	0.8
16	6.0	0.8
17	6.4	0.8
18	6.8	0.8
19	7.2	0.8
20	7.6	0.8
21	8.0	0.8
22	8.4	0.8
23	8.8	0.8
24	9.2	0.8
25	9.6	0.8
26	10.0	0.8
27	10.4	0.8
28	10.8	0.8
29	11.2	0.8
30	11.6	0.8
31	12.0	0.8
32	13.6	0.8
33	15.2	0.8
34	16.8	0.8
35	18.4	0.8
36	20.0	0.8

(a)

Row #	Option A: Fixed Pay	Option B: Tournament
1	0.0	3.2
2	0.4	3.2
3	0.8	3.2
4	1.2	3.2
5	1.6	3.2
6	2.0	3.2
7	2.4	3.2
8	2.8	3.2
9	3.2	3.2
10	3.6	3.2
11	4.0	3.2
12	4.4	3.2
13	4.8	3.2
14	5.2	3.2
15	5.6	3.2
16	6.0	3.2
17	6.4	3.2
18	6.8	3.2
19	7.2	3.2
20	7.6	3.2
21	8.0	3.2
22	8.4	3.2
23	8.8	3.2
24	9.2	3.2
25	9.6	3.2
26	10.0	3.2
27	10.4	3.2
28	10.8	3.2
29	11.2	3.2
30	11.6	3.2
31	12.0	3.2
32	13.6	3.2
33	15.2	3.2
34	16.8	3.2
35	18.4	3.2
36	20.0	3.2

(b)

Row #	Option A: Fixed Pay	Option B: Lump-sum
1	0.0	6.4
2	0.1	6.4
3	0.3	6.4
4	0.4	6.4
5	0.5	6.4
6	0.7	6.4
7	0.8	6.4
8	0.9	6.4
9	1.1	6.4
10	1.2	6.4
11	1.3	6.4
12	1.5	6.4
13	1.6	6.4
14	1.7	6.4
15	1.9	6.4
16	2.0	6.4
17	2.1	6.4
18	2.3	6.4
19	2.4	6.4
20	2.5	6.4
21	2.7	6.4
22	2.8	6.4
23	2.9	6.4
24	3.1	6.4
25	3.2	6.4
26	3.3	6.4
27	3.5	6.4
28	3.6	6.4
29	3.7	6.4
30	3.9	6.4
31	4.0	6.4
32	4.4	6.4
33	4.8	6.4
34	5.2	6.4
35	5.6	6.4
36	6.0	6.4

(c)

Row #	Option A: Tournament	Option B: Piece Rate
1	0.0	0.8
2	0.2	0.8
3	0.4	0.8
4	0.6	0.8
5	0.8	0.8
6	1.0	0.8
7	1.2	0.8
8	1.4	0.8
9	1.6	0.8
10	1.8	0.8
11	2.0	0.8
12	2.2	0.8
13	2.4	0.8
14	2.6	0.8
15	2.8	0.8
16	3.0	0.8
17	3.2	0.8
18	3.4	0.8
19	3.6	0.8
20	3.8	0.8
21	4.0	0.8
22	4.2	0.8
23	4.4	0.8
24	4.6	0.8
25	4.8	0.8
26	5.0	0.8
27	5.2	0.8
28	5.4	0.8
29	5.6	0.8
30	5.8	0.8
31	6.0	0.8
32	6.4	0.8
33	6.8	0.8
34	7.2	0.8
35	7.6	0.8
36	8.0	0.8

(d)

Row #	Option A:Piece Rate	Option B: Tournament
1	0.0	3.2
2	0.1	3.2
3	0.2	3.2
4	0.3	3.2
5	0.4	3.2
6	0.5	3.2
7	0.6	3.2
8	0.7	3.2
9	0.8	3.2
10	0.9	3.2
11	1.0	3.2
12	1.1	3.2
13	1.2	3.2
14	1.3	3.2
15	1.4	3.2
16	1.5	3.2
17	1.6	3.2
18	1.7	3.2
19	1.8	3.2
20	1.9	3.2
21	1.9	3.2
22	2.0	3.2
23	2.1	3.2
24	2.2	3.2
25	2.3	3.2
26	2.4	3.2
27	2.5	3.2
28	2.6	3.2
29	2.7	3.2
30	2.8	3.2
31	2.9	3.2
32	3.2	3.2
33	4.0	3.2
34	4.8	3.2
35	5.6	3.2
36	6.4	3.2

(e)

Figure H.4: MPLs for stage 6 at low base-payoff (piece rate = 0.8, tournament = 3.2)

Row #	Option A: Fixed Pay	Option B: Piece Rate
1	0	1.6
2	0.8	1.6
3	1.6	1.6
4	2.4	1.6
5	3.2	1.6
6	4.0	1.6
7	4.8	1.6
8	5.6	1.6
9	6.4	1.6
10	7.2	1.6
11	8.0	1.6
12	8.8	1.6
13	9.6	1.6
14	10.4	1.6
15	11.2	1.6
16	12.0	1.6
17	12.8	1.6
18	13.6	1.6
19	14.4	1.6
20	15.2	1.6
21	16.0	1.6
22	16.8	1.6
23	17.6	1.6
24	18.4	1.6
25	19.2	1.6
26	20.0	1.6
27	20.8	1.6
28	21.6	1.6
29	22.4	1.6
30	23.2	1.6
31	24.0	1.6
32	27.2	1.6
33	30.4	1.6
34	33.6	1.6
35	36.8	1.6
36	40.0	1.6

(a)

Row #	Option A: Fixed Pay	Option B: Tournament
1	0	6.4
2	0.8	6.4
3	1.6	6.4
4	2.4	6.4
5	3.2	6.4
6	4.0	6.4
7	4.8	6.4
8	5.6	6.4
9	6.4	6.4
10	7.2	6.4
11	8.0	6.4
12	8.8	6.4
13	9.6	6.4
14	10.4	6.4
15	11.2	6.4
16	12.0	6.4
17	12.8	6.4
18	13.6	6.4
19	14.4	6.4
20	15.2	6.4
21	16.0	6.4
22	16.8	6.4
23	17.6	6.4
24	18.4	6.4
25	19.2	6.4
26	20.0	6.4
27	20.8	6.4
28	21.6	6.4
29	22.4	6.4
30	23.2	6.4
31	24.0	6.4
32	27.2	6.4
33	30.4	6.4
34	33.6	6.4
35	36.8	6.4
36	40.0	6.4

(b)

Row #	Option A: Fixed Pay	Option B: Lump-sum
1	0	12.8
2	0.3	12.8
3	0.5	12.8
4	0.8	12.8
5	1.1	12.8
6	1.3	12.8
7	1.6	12.8
8	1.9	12.8
9	2.1	12.8
10	2.4	12.8
11	2.7	12.8
12	2.9	12.8
13	3.2	12.8
14	3.5	12.8
15	3.7	12.8
16	4.0	12.8
17	4.3	12.8
18	4.5	12.8
19	4.8	12.8
20	5.1	12.8
21	5.3	12.8
22	5.6	12.8
23	5.9	12.8
24	6.1	12.8
25	6.4	12.8
26	6.7	12.8
27	6.9	12.8
28	7.2	12.8
29	7.5	12.8
30	7.7	12.8
31	8.0	12.8
32	8.8	12.8
33	9.6	12.8
34	10.4	12.8
35	11.2	12.8
36	12.0	12.8

(c)

Row #	Option A: Tournament	Option B: Piece Rate
1	0	1.6
2	0.4	1.6
3	0.8	1.6
4	1.2	1.6
5	1.6	1.6
6	2.0	1.6
7	2.4	1.6
8	2.8	1.6
9	3.2	1.6
10	3.6	1.6
11	4.0	1.6
12	4.4	1.6
13	4.8	1.6
14	5.2	1.6
15	5.6	1.6
16	6.0	1.6
17	6.4	1.6
18	6.8	1.6
19	7.2	1.6
20	7.6	1.6
21	8.0	1.6
22	8.4	1.6
23	8.8	1.6
24	9.2	1.6
25	9.6	1.6
26	10.0	1.6
27	10.4	1.6
28	10.8	1.6
29	11.2	1.6
30	11.6	1.6
31	12.0	1.6
32	12.8	1.6
33	13.6	1.6
34	14.4	1.6
35	15.2	1.6
36	16.0	1.6

(d)

Row #	Option A:Piece Rate	Option B: Tournament
1	0	6.4
2	0.2	6.4
3	0.4	6.4
4	0.6	6.4
5	0.9	6.4
6	1.1	6.4
7	1.28	6.4
8	1.5	6.4
9	1.7	6.4
10	1.8	6.4
11	2.0	6.4
12	2.2	6.4
13	2.4	6.4
14	2.6	6.4
15	2.8	6.4
16	3.0	6.4
17	3.1	6.4
18	3.3	6.4
19	3.52	6.4
20	3.7	6.4
21	3.9	6.4
22	4.1	6.4
23	4.3	6.4
24	4.5	6.4
25	4.64	6.4
26	4.8	6.4
27	5.0	6.4
28	5.2	6.4
29	5.4	6.4
30	5.6	6.4
31	5.8	6.4
32	6.4	6.4
33	8.0	6.4
34	9.6	6.4
35	11.2	6.4
36	12.8	6.4

(e)

Figure H.5: MPLs for stage 6 at median base-payoff (piece rate = 1.6, tournament = 6.4)

Row #	Option A: Fixed Pay	Option B: Piece Rate
1	0	2.4
2	1.2	2.4
3	2.4	2.4
4	3.6	2.4
5	4.8	2.4
6	6.0	2.4
7	7.2	2.4
8	8.4	2.4
9	9.6	2.4
10	10.8	2.4
11	12.0	2.4
12	13.2	2.4
13	14.4	2.4
14	15.6	2.4
15	16.8	2.4
16	18.0	2.4
17	19.2	2.4
18	20.4	2.4
19	21.6	2.4
20	22.8	2.4
21	24.0	2.4
22	25.2	2.4
23	26.4	2.4
24	27.6	2.4
25	28.8	2.4
26	30.0	2.4
27	31.2	2.4
28	32.4	2.4
29	33.6	2.4
30	34.8	2.4
31	36.0	2.4
32	40.8	2.4
33	45.6	2.4
34	50.4	2.4
35	55.2	2.4
36	60.0	2.4

(a)

Row #	Option A: Fixed Pay	Option B: Tournament
1	0	9.6
2	1.2	9.6
3	2.4	9.6
4	3.6	9.6
5	4.8	9.6
6	6.0	9.6
7	7.2	9.6
8	8.4	9.6
9	9.6	9.6
10	10.8	9.6
11	12.0	9.6
12	13.2	9.6
13	14.4	9.6
14	15.6	9.6
15	16.8	9.6
16	18.0	9.6
17	19.2	9.6
18	20.4	9.6
19	21.6	9.6
20	22.8	9.6
21	24.0	9.6
22	25.2	9.6
23	26.4	9.6
24	27.6	9.6
25	28.8	9.6
26	30.0	9.6
27	31.2	9.6
28	32.4	9.6
29	33.6	9.6
30	34.8	9.6
31	36.0	9.6
32	40.8	9.6
33	45.6	9.6
34	50.4	9.6
35	55.2	9.6
36	60.0	9.6

(b)

Row #	Option A: Fixed Pay	Option B: Lump-sum
1	0	19.2
2	0.4	19.2
3	0.8	19.2
4	1.2	19.2
5	1.6	19.2
6	2.0	19.2
7	2.4	19.2
8	2.8	19.2
9	3.2	19.2
10	3.6	19.2
11	4.0	19.2
12	4.4	19.2
13	4.8	19.2
14	5.2	19.2
15	5.6	19.2
16	6.0	19.2
17	6.4	19.2
18	6.8	19.2
19	7.2	19.2
20	7.6	19.2
21	8.0	19.2
22	8.4	19.2
23	8.8	19.2
24	9.2	19.2
25	9.6	19.2
26	10.0	19.2
27	10.4	19.2
28	10.8	19.2
29	11.2	19.2
30	11.6	19.2
31	12.0	19.2
32	13.2	19.2
33	14.4	19.2
34	15.6	19.2
35	16.8	19.2
36	18.0	19.2

(c)

Row #	Option A: Tournament	Option B: Piece Rate
1	0	2.4
2	0.6	2.4
3	1.2	2.4
4	1.8	2.4
5	2.4	2.4
6	3.0	2.4
7	3.6	2.4
8	4.2	2.4
9	4.8	2.4
10	5.4	2.4
11	6.0	2.4
12	6.6	2.4
13	7.2	2.4
14	7.8	2.4
15	8.4	2.4
16	9.0	2.4
17	9.6	2.4
18	10.2	2.4
19	10.8	2.4
20	11.4	2.4
21	12.0	2.4
22	12.6	2.4
23	13.2	2.4
24	13.8	2.4
25	14.4	2.4
26	15.0	2.4
27	15.6	2.4
28	16.2	2.4
29	16.8	2.4
30	17.4	2.4
31	18.0	2.4
32	19.2	2.4
33	20.4	2.4
34	21.6	2.4
35	22.8	2.4
36	24.0	2.4

(d)

Row #	Option A:Piece Rate	Option B: Tournament
1	0	9.6
2	0.3	9.6
3	0.6	9.6
4	1.0	9.6
5	1.3	9.6
6	1.6	9.6
7	1.92	9.6
8	2.2	9.6
9	2.5	9.6
10	2.8	9.6
11	3.0	9.6
12	3.3	9.6
13	3.6	9.6
14	3.9	9.6
15	4.2	9.6
16	4.4	9.6
17	4.7	9.6
18	5.0	9.6
19	5.28	9.6
20	5.6	9.6
21	5.8	9.6
22	6.1	9.6
23	6.4	9.6
24	6.7	9.6
25	6.96	9.6
26	7.2	9.6
27	7.5	9.6
28	7.8	9.6
29	8.1	9.6
30	8.4	9.6
31	8.6	9.6
32	9.6	9.6
33	12	9.6
34	14.4	9.6
35	16.8	9.6
36	19.2	9.6

(e)

Figure H.6: MPLs for stage 6 at high base-payoff (piece rate = 2.4, tournament = 9.6)

Option A	Option B	Decision
Fixed Pay $0	Tournament $3.2	○ ◉
Fixed Pay $2.4	Tournament $3.2	○ ◉
Fixed Pay $4.8	Tournament $3.2	○ ◉
Fixed Pay $7.2	Tournament $3.2	◉ ○
Fixed Pay $9.6	Tournament $3.2	◉ ○
Fixed Pay $12.0	Tournament $3.2	◉ ○

Continue

(a) Sub-choice table 1 Multiple Price List with a Valid Switching Point

Option A	Option B	Decision
Fixed Pay $ 4.8	Tournament $ 3.2	○ ◉
Fixed Pay $ 5.2	Tournament $ 3.2	○ ◉
Fixed Pay $ 5.6	Tournament $ 3.2	○ ◉
Fixed Pay $ 6.0	Tournament $ 3.2	◉ ○
Fixed Pay $ 6.4	Tournament $ 3.2	◉ ○
Fixed Pay $ 6.8	Tournament $ 3.2	◉ ○

Continue

(b) Sub-choice table 2 Multiple Price List

Option A	Option B	Decision
Fixed Pay $0	Tournament $3.2	○ ◉
Fixed Pay $2.4	Tournament $3.2	○ ◉
Fixed Pay $4.8	Tournament $3.2	○ ◉
Fixed Pay $7.2	Tournament $3.2	○ ◉
Fixed Pay $9.6	Tournament $3.2	○ ◉
Fixed Pay $12.0	Tournament $3.2	○ ◉

Continue

(c) Sub-choice table 1 Multiple Price List with All B

Option A	Option B	Decision
Fixed Pay $ 12.0	Tournament $ 3.2	○ ○
Fixed Pay $ 13.6	Tournament $ 3.2	○ ○
Fixed Pay $ 15.2	Tournament $ 3.2	○ ○
Fixed Pay $ 16.8	Tournament $ 3.2	○ ○
Fixed Pay $ 18.4	Tournament $ 3.2	○ ○
Fixed Pay $ 20.0	Tournament $ 3.2	○ ○

Continue

(d) Sub-choice table 2 Multiple Price List with All B

Figure H.7: Examples of iterated MPL and non-switchers

Appendix I Instruction manual

Welcome to our study on decision making. Before we begin the experiment, please take several minutes to carefully read these instructions. These instructions will also be provided throughout the experiment, when applicable. Each participant will receive a $5 show up fee and $7 completion fee in addition to additional payment depending on performance and choices you make during the experiment. All information provided will be kept confidential and will be used for research purposes only. Please refrain from discussing any aspect of the specific tasks of the study with anyone.

- It is important to read the instructions carefully so that you understand the tasks in making your decisions.
- If you are done with a certain part and have the option of clicking 'Continue,' please do so to continue with the experiment.
- Please turn off your cellphone.
- Please do not communicate with others during the experiment.
- At any time, if you have questions, please raise your hand.

I.1 Addition task

In this study, you will be asked to perform a number of Addition Tasks. In each Addition Task, you will calculate the sum of five randomly chosen two-digit numbers. Below is an example.

In each Addition Task, you will be given 3 minutes to calculate as many sums as possible. You cannot use a calculator (including cellphone), however, you are welcome to use the provided scratch paper. Once you enter your answer to the sum of these five numbers in the provided box, please submit your answer by clicking submit with your mouse. NOTE: you can use the number pad or the numbers at the top of the keyboard to enter your answer, but you CANNOT press 'ENTER' to submit, and must click on the red "Submit" button with your mouse. After you enter your answer, you will be notified regarding whether you got the question correct and will be given a new set of five numbers to add. Continue answering these problems until the time runs out — in order to maximize payment, it is in your best interest to answer as many correctly as possible in the allotted time. You will be told your performance after you complete an Addition Task. Your performance will not be shared with other participants, and will only be revealed to you.

I.2 Payment scheme

There are 4 types of payment schemes which could be applied to the aforementioned Addition Tasks.

Fixed Pay: Under this scheme, your payment will be a fixed pay price and will not depend on your score on the Addition Task. Note that the fixed pay price may vary across tasks. For example, under fixed pay of $1, no matter how many questions you correctly compute in an Addition Task, you will receive $1.

Piece Rate: Under this scheme, your payment will be a piece rate price multiplied by the number of questions you solve correctly in a 3 minute Addition Task. Your payment does not decrease if you provide an incorrect answer to a problem. Hence under Piece Rate, your payment is computed as: Payment = piece rate price x number of correct answers. For example, if you correctly compute 4 questions in an Addition Task, at piece rate price $2, your pay will be $2 x 4 = $8. Please note that the piece rate price may vary across tasks.

Tournament: Under this scheme, your payment depends on your performance relative to that of a group of other participants. In this experiment, all tournaments consist of FOUR people randomly chosen in the room, and the group composition is fixed at the start of the experiment. You will not be told who is in your group. If you solve the highest number of problems in your group, you will receive the tournament price per correct problem, otherwise you receive no payment. If you tie for the highest score, you still receive the tournament price per correct problems. Hence under Tournament, your payment is computed as Payment = Tournament price x number of correct answers if you win (i.e. solve the most correct problems irrespective of ties); and Payment = 0 if you lose (i.e. at least one of the other four members scored higher than you). For example, if you correctly compute 4 questions in a round and the other three members in your group correctly compute 3, you win the tournament. Supposing the tournament price is $2 per correct question, your pay will be $2 x 4 = $8. If one other member also scored 4, your pay will still be $2 x 4 = $8. If you correctly compute 4 questions and one of the other three members in your group correctly computes 5 questions, you lose the tournament, and your pay will be $0. Please note that the tournament price also varies across tasks and the price per question correct is typically higher than piece rate.

Lumpsum Tournament: Under this scheme, if you win a tournament as described above, you will receive a lumpsum payment; and Payment = $0 if you lose. The amount of lumpsum payment does not depend on the number of questions you correctly compute. For example, if you correctly compute 4 questions in a round and the other three members in your group correctly compute 3, you win the tournament. Suppose the lumpsum price is $10, then your pay will be $10, and that pay will be the same irrespective of how many questions you answered correctly as long as you have the most correct answers in your group. If one other member also scored 4, your pay will still be $10. If you correctly compute 4 questions and one of the other three members in your group correctly computes 5 questions, you lose the tournament, and your pay will be $0.

I.3 Choice table

In a Choice Table, you will be asked to choose between two of the four aforementioned payment schemes to apply to a given Addition Task you completed or will complete. The Addition Task in question will be made clear during the experiment. Option A indicates one payment scheme, and Option B indicates another payment scheme. In each table, the payment schemes for Option A and Option B vary, and the specific prices will be explicitly given. For each row, you will choose whether you prefer Option A or Option B. In most Choice Tables, Option B will be a constant value under a given pay scheme, and Option A will be increasing under another pay scheme. Note that when filling out each single choice table, you will have up to 35 seconds to make a decision for each row. For the purpose of maximizing your payment, it is crucial that you make a choice for each row before the timer runs out. Although the timers should provide you ample time to fill out the rows, if you take too long on a choice table, you may run out of time. If a row that is left blank is chosen for payment, you will receive $0 from it, so it is in your interest to move at a good pace while making the choices that are preferable to you. When you finish filling out a Choice Table, click 'Continue' to move on. There are 36 choices to be made in each Choice Table. If a Choice Table is chosen for payment, one out of 36 choices will be randomly selected for payment. As each choice you made in a Choice Table has a chance to be applied to compute your total payoff for this experiment, it is in your best interest to make each choice carefully. Below is an example of a Choice Table. Choice Tables are all similar, except that the payment schemes and amounts in Option A and Option B change depending on the Choice Table. As can be seen, for each row, you will be asked to choose whether you prefer Option A or Option B. The experiment will make clear what you are applying these payments towards.

Example: Choice Table: Between Fixed Pay and Tournament

There are five types of main Choice Tables. Type 1 Choice Table: This table elicits your preference between Fixed Pay and Piece Rate. For this choice table, the payoff for Option A (Fixed Pay scheme) increases in each row, and the payoff for Option B (Piece Rate scheme) is constant. For each row, you must choose which of the two options you prefer in the final "Decision" column – A or B – by clicking on the one you prefer.

Type 2 Choice Table: This table elicits your preference between Fixed Pay and Tournament. For this choice table, the payoff for Option A (Fixed Pay scheme) increases in payoff in each row, and the payoff for Option B (Tournament scheme) is constant. For each row, you must choose which of the two options you prefer in the final "Decision" column – A or B – by clicking on the one you prefer.

Type 3 Choice Table: This table elicits your preference between Tournament and Piece Rate. For this choice table, the payoff for Option A (Tournament scheme) increases in payoff in each row, and the payoff for Option B (Piece Rate scheme) is constant. For each row, you must choose which of the two options you prefer in the final "Decision" column – A or B – by clicking on the one you prefer.

Type 4 Choice Table: This table elicits your preference between Piece Rate and Tournament. For this choice table, the payoff for Option A (Piece Rate scheme) increases in payoff in each row, and the payoff for Option B (Tournament scheme) is constant. For each row, you must choose which of the two options you prefer in the final "Decision" column – A or B – by clicking on the one you prefer.

Type 5 Choice Table: This table elicits your preference between Fixed Pay and Lumpsum Tournament. For this choice table, the payoff for Option A (Fixed Pay scheme) increases in payoff in each row, and the payoff for Option B (Lumpsum Tournament scheme) is constant. For each row, you must choose which of the two options you prefer in the final "Decision" column – A or B – by clicking on the one you prefer.

Note: In order to make the decision process easier for you, in this experiment, we adopt a "two-stage choice table" design. Each choice table contains 2 sub-choice tables. Since Option B is fixed, and Option A increases in amount as you go down the rows, you may decide to switch from Option B to Option A at some point. After making your decisions for each row and clicking 'Continue', you will then be prompted with a sub-table 2 which contains more refined grids than sub-table 1 with choices in between the two points where you switched from Option B to Option A.

Additionally, there are a few choice tables that are unrelated to your performance in past or future addition tasks, but instead elicit your preference between two different Options. These choice tables will be explained fully when they appear, and follow the same concept as the previous choice tables and ask you, for each row, to make a decision between Option A and Option B.

I.4 Experiment flow

Next, we will explain the flow of this experiment. The experiment consists of 10 parts. Each part contains multiple sub-parts. Part 1 includes 2 rounds of practice addition tasks as well as a pre-experiment questionnaire. Parts 2, 3, and 4 each contain two rounds of addition tasks and 4 sets of choice tables for your performance on these past two rounds of addition tasks. Parts 5, 6 and 7 each contain 4 sets of choice tables for future performance. Part 8 asks you to guess your relative ranking in addition tasks as well as some risk preference questions. Part 9 is a short survey questionnaire. Part 10 is a potential final addition task. The experiment takes about 1 hour to complete. It is important that you finish ALL parts of the experiment.

I.5 Payment calculation

Your payment total will be calculated as follows: You will receive a minimum of $12 for fully completing the experiment. In addition to this sum, certain sub-parts in the pre-survey question and rank guess parts have payments that may depend on your performance on the addition tasks and the choices you make. It will be made clear when a part involves payment.

In addition to the above two payments, one sub-part from parts 2-7 will be randomly selected for payment.

- If the randomly selected sub-part is an Addition Task, then you will be paid depending on the type of Addition Task. For example, if the Addition Task is under a Piece Rate scheme at price $1, you will be paid $1 x number of correct answers.

- If the randomly selected sub-part is a choice table, one of the rows will be randomly chosen for payment. For this randomly chosen row, you will be paid given the choice you made between Option A and Option B. Recall that the choice tables are timed (35 seconds per sub choice table). Although this should be plenty of time to fill out each choice table, if you run out of time and a row that you did not complete is selected for payment, your payment for this part will be $0. As such, you should be sure to complete the choice tables in the allotted time.

Your final payment will be rounded up to the nearest 25 cents. So if your final pay is $25.05, you will receive $25.25.

To maximize your profit, it is important to finish all parts. It is also important to make your preferred decision for each row in the Choice Tables while moving at a good pace and perform well in the Addition Tasks.

ONCE YOU HAVE FINISHED READING THE INSTRUCTIONS, PLEASE PRESS “CONTINUE” ON THE SCREEN. ONCE EVERYONE HAS DONE SO, THE EXPERIMENT WILL BEGIN.

Appendix References

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