A Structural Analysis of Disappointment Aversion in a Real Effort Competition*

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First Version: September 5th 2009

This Version: September 1st 2010

Abstract

We develop a novel computerized real effort task, based on moving sliders across a screen, to test experimentally whether agents are disappointment averse when they compete in a real effort sequential-move tournament. We predict that a disappointment averse agent, who is loss averse around her endogenous choice-acclimating expectations-based reference point, responds negatively to her rival's effort. We find significant evidence for this discouragement effect, and use the Method of Simulated Moments to estimate the strength of disappointment aversion on average and the heterogeneity in disappointment aversion across the population.

Keywords: Disappointment aversion; Loss aversion; Reference-dependent preferences; Reference point adjustment; Expectations; Tournament; Real effort experiment; Slider task.

JEL Classification: C91; D03.

*We would like to thank the University of Arizona, where this research was completed, the Nuffield Centre for Experimental Social Sciences for hosting our experiment, the Oxford Supercomputing Centre for providing computational facilities, and the George Webb Medley Fund and Southampton University's School of Social Sciences for funding our experiment.

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1 Introduction

Disappointment at doing worse than expected can be a powerful emotion. This emotion may be particularly intense when the disappointed agent exerted effort in competing for a prize, thus raising her expectation of winning. Furthermore, a rational agent who anticipates possible disappointment will optimize taking into account the expected disappointment arising from her choice.

In this paper we use a laboratory experiment to test whether agents are disappointment averse when they compete in a real effort tournament. In particular, we test whether our subjects are loss averse around reference points given by endogenous expectations which adjust to both an agent's own effort choice and that of her rival. Pairs of subjects complete a novel computerized real effort task, called the "slider task", which involves moving sliders across a screen. The *First Mover* completes the task, followed by the *Second Mover*, who observes the First Mover's effort before choosing how hard to work.[1] A money prize is awarded to one of the pair members based on the pair's relative work efforts and some element of chance which we control. After each repetition, the subjects are re-paired. We impose probabilities of winning the prize which are linear in the difference in the agents' efforts, so the marginal impact of a Second Mover's effort on her probability of winning does not depend on the effort of the First Mover she is paired with. Therefore, if agents care only about money and their cost of effort, the Second Mover's work effort should not depend on the effort of the First Mover. However, as predicted by our model of disappointment aversion, the experimental data show a *discouragement effect*: the Second Mover shies away from working hard when she observes that the First Mover has worked hard, and tends to work relatively hard when she observes that her competitor has put in low effort. Thus First and Second Movers' efforts are strategic substitutes.

Our primary contribution is empirical. First, we offer evidence consistent with disappointment aversion from a reduced form linear random effects panel regression. More substantively, we exploit the richness of our experimental data set to estimate the parameters of a structural model of disappointment aversion using the Method of Simulated Moments. This allows us to estimate the strength of disappointment aversion on average and the extent of heterogeneity in disappointment aversion across the population. Goodness of fit analysis shows that the estimated model fits our data well.

Together with random variation in the monetary prize across pairs of subjects, the design of our slider task generates sufficient variation in behavior to enable us to estimate the structural parameters of our model of disappointment aversion. In particular, the slider task gives a finely gradated measure of performance over a short time scale. As the task takes only two minutes to complete, we can collect repeated observations of the same Second Movers facing different prizes and First Mover efforts, while the fineness of the performance measure allows us to observe accurately how Second Movers respond to different prizes and First Mover efforts. The resulting panel data permit precise quantification of the distribution of the cost of effort and the strength of disappointment aversion across agents in the population.

The formal model that we test is a natural extension of disappointment aversion to situations

[1] We use a sequential tournament to give clean identification, rather than because most competitive situations involve sequential effort choices.

in which agents compete. Models of disappointment aversion (e.g., Bell, 1985; Loomes and Sugden, 1986; Delquié and Cillo, 2006; Kőszegi and Rabin, 2006, 2007) build on the idea that agents are sensitive to deviations from what they expected to receive; in particular, agents are loss averse around their expected payoff so losses relative to this expectation are more painful than equal-sized gains are pleasurable. We model expectations-based reference points as adjusting to an agent's own effort choice and that of her rival: in the terminology of Kőszegi and Rabin (2007) they are choice-acclimating. The endogeneity of an agent's reference point is crucial: with loss aversion around a fixed reference point, even if given by a prior expectation, a Second Mover will continue to disregard First Mover effort.

Our empirical results thus address two important open questions in the literature on reference-dependent preferences: (i) what constitutes agents' reference points?; and (ii) how quickly do these reference points adjust to new circumstances? Our analysis provides evidence that when agents compete they have reference points given by their expected monetary payoff and that an agent's reference point adjusts essentially instantaneously to her own effort choice and that of her competitor.

Abeler et al. (2009) also provide reduced form evidence consistent with choice-acclimating reference-dependent preferences in the context of effort provision. Abeler et al. run a laboratory experiment in which subjects have a 50% chance of being paid piece-rate and a 50% chance of receiving a fixed payment, and show that effort increases in the fixed payment. To the best of our knowledge, however, we are the first to estimate the strength of loss aversion around choice-acclimating reference points when agents exert effort. Furthermore, we are able to leverage our structural analysis to provide evidence that the expectation which acts as the reference point adjusts to the agent's own choice of effort. In contrast, Abeler et al. (2009) do not distinguish between their choice-acclimating model and a more parsimonious model in which the reference point adjusts to the fixed payment but not the agent's actual effort choice. Finally, we provide evidence that choice-acclimating reference points are important in a different context to Abeler et al., namely one in which agents work to influence their probability of success. Such situations are common: in labor markets, workers often exert effort to increase their chances of winning promotions and bonuses; while agents also work to make success more likely in sports contests, examinations, patent races and elections.

Complementary to our laboratory findings, Doran (2009), Pope and Schweitzer (2009) and Crawford and Meng (2010) find evidence of expectations-based reference-dependent preferences when cab drivers and professional golfers exert effort in the field.[2] In particular, Crawford and Meng (2010) estimate the average strength of loss aversion for cab drivers around rational expectations-based daily income and hours targets. In contrast to our model, in these papers the reference point is taken to be fixed when the agents choose how hard to work, and so is not choice-acclimating. Evidence of expectations-based reference points in the absence of effort provision includes Loomes and Sugden (1987) and Choi et al. (2007), who study choices over lotteries, Post et al. (2008), who find evidence that reference points adjust during the course of the game show "Deal or No Deal", Card and Dahl (2010), who show that the probability of domestic violence

[2] An earlier literature in which reference points do not adjust to expectations explicitly also finds evidence of reference-dependent preferences in the field; for example, Camerer et al. (1997) study cab drivers and Fehr and Götte (2007) analyze bike messengers.

when an NFL football team loses depends on the extent to which the loss was expected, and Ericson and Fuster (2010), who find that the valuation placed on an endowed good depends on the probability that a trading opportunity will arise. The psychology literature also supports the thesis that agents' emotional responses to the outcomes of gambles include disappointment and elation, that agents anticipate these emotions when choosing between gambles and that exerting effort, by increasing the likelihood of a good outcome, intensifies disappointment (Mellers et al., 1999; van Dijk et al., 1999).

Finally, our finding of a Second Mover discouragement effect adds to the existing literature on laboratory tournaments by showing that non-standard preferences can move behavior away from that predicted by standard theory and by providing evidence of the impact of feedback during tournaments. Charness and Kuhn (2010) summarize the experimental literature: Bull et al. (1987) study tournaments with an induced cost of effort; van Dijk et al. (2001) introduce real effort; while Berger and Pope (2009) and Eriksson et al. (2009) consider feedback.

The rest of the paper is structured as follows. Section 2 describes the slider task and the design of the experiment. Section 3 develops our model of disappointment aversion when agents compete. Section 4 presents the empirical analysis. Section 5 discusses alternative behavioral explanations of the discouragement effect. Section 6 concludes. Appendix A derives proofs not included in the main text. Appendix B provides further details about the structural estimation method and the model's goodness of fit. Finally, Appendix C [intended for online publication] lays out the instructions provided to the experimental subjects.

2 Experimental Design

We ran 6 experimental sessions at the Nuffield Centre for Experimental Social Sciences (CESS) in Oxford, all conducted on weekdays at the same time of day in late February and early March 2009 and lasting approximately 90 minutes.[3] 20 student subjects (who did not report Psychology or Economics as their main subject of study) participated in each session, with 120 participants in total. The subjects were drawn from the CESS subject pool which is managed using the Online Recruitment System for Economic Experiments (ORSEE). The experimental instructions (Appendix C) were provided to each subject in written form and were read aloud to the subjects. Seating positions were randomized. To ensure subject-experimenter anonymity, actions and payments were linked to randomly allocated Participant ID numbers. Each subject was paid a show-up fee of £4 and earned an average of a further £10 during the experiment (all payments were in Pounds sterling). Subjects were paid privately in cash by the laboratory administrator. The experiment was programmed in z-Tree (Fischbacher, 2007).

2.1 The Slider Task

Before setting out the experimental procedure, we first describe the novel computerized real effort task, which we call the "slider task", that we designed for the purpose of this experiment.

The slider task consists of a single screen displaying a number of sliders. The number and position of the sliders on the screen does not vary across experimental subjects or across

[3] We also ran one pilot session without any monetary incentives whose results are not reported here.

repetitions of the task. A schematic representation of a single slider is shown in Figure 1. When the screen containing the effort task is first displayed to the subject all of the sliders are positioned at 0, as shown for a single slider in Figure 1(a). By using the mouse, the subject can position each slider at any integer location between 0 and 100 inclusive. Each slider can be adjusted and readjusted an unlimited number of times and the current position of each slider is displayed to the right of the slider. The subject's "points score" in the task is the number of sliders positioned at 50 at the end of the allotted time. Figure 1(b) shows a correctly positioned slider. As the task proceeds, the screen displays the subject's current points score and the amount of time remaining.

(a) Initial position. (b) Positioned at 50.

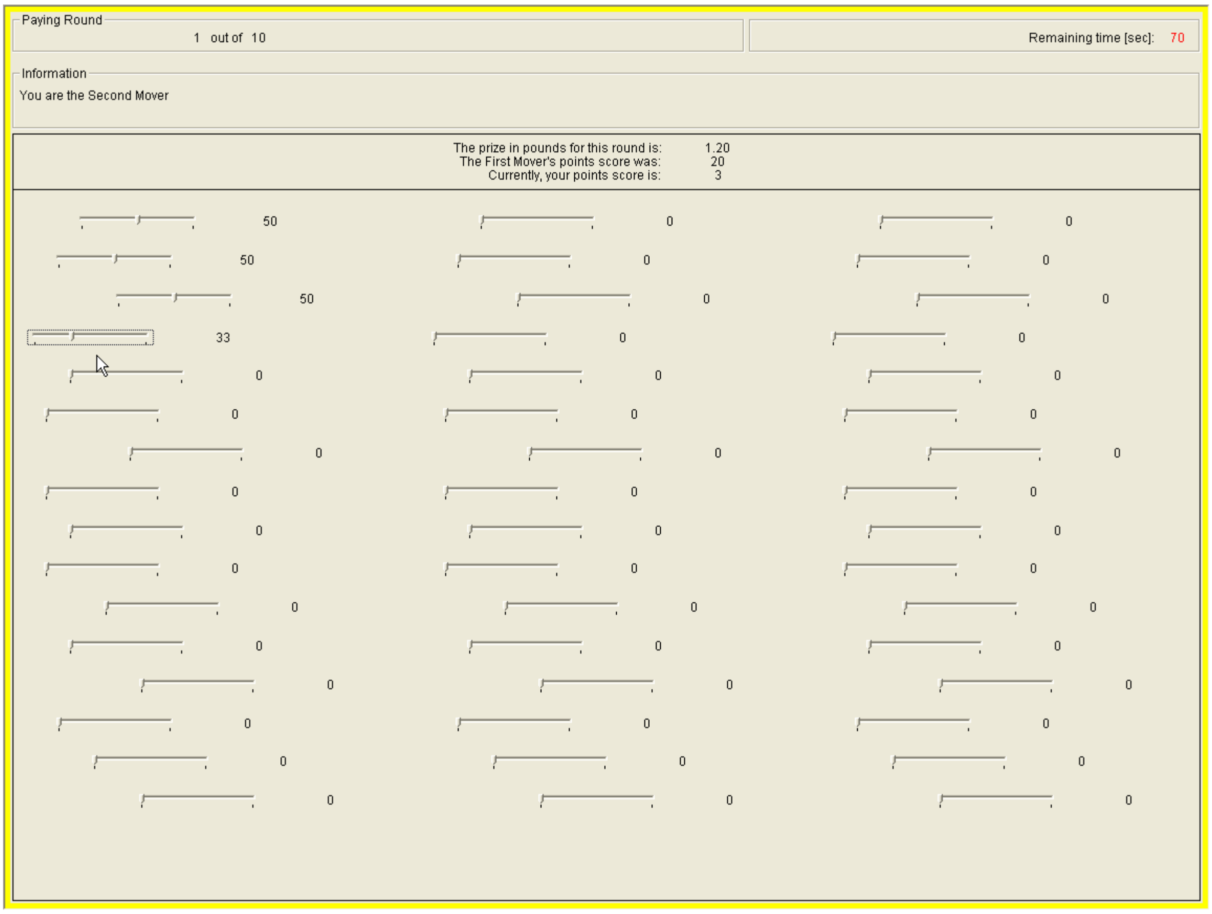
Figure 1: Schematic representation of a slider.

The number of sliders and task length can be chosen by the experimenter. In this experiment we used 48 sliders and an allotted time of 120 seconds. The sliders were displayed on 22 inch widescreen monitors with a 1680 by 1050 pixel resolution. To move the sliders, the subjects used 800 dpi USB mice with the scroll wheel disabled.[4] Figure 2 shows a screen of sliders as shown to the subject in the laboratory. In this example, the subject has positioned three of the sliders at 50 and a points score of 3 is shown at the top of the screen. A fourth slider is currently positioned at 33 and this slider does not contribute to the subject's points score as it is not positioned correctly. To ensure that all the sliders are equally difficult to position correctly, the 48 sliders are arranged on the screen such that no two sliders are aligned exactly one under the other. This prevents the subject being able to position the higher slider at 50 and then easily position the lower slider by copying the position of the higher slider.

The slider task gives a finely gradated measure of performance and involves little randomness; thus we interpret a subject's point score as effort exerted in the task. In Section 4 we see that with 48 sliders and an allotted time of 120 seconds, measured effort varies from 0 to 41, so the task gives rise to substantial variation in behavior, and hence we can observe accurately how Second Movers respond to different prizes and First Mover efforts. As the task takes only two minutes to complete, we can collect repeated observations of the same Second Movers facing different prizes and First Mover efforts, allowing us to control for persistent unobserved heterogeneity. The resulting panel data enable us to use structural estimation to quantify precisely the distribution of the cost of effort and the strength of disappointment aversion across agents in the population.

The slider task also has a number of other desirable attributes: it is simple to communicate and to understand; it does not require or test pre-existing knowledge; it is identical across repetitions; there is no scope for guessing; and as the task is computerized, it is easy to implement and allows flexible real-time subject interactions.

[4]The keyboards were also disabled to prevent the subjects using the arrow keys to position the sliders.



Notes: The screen presented here is slightly squarer than the one seen by our subjects.

Figure 2: Screen showing 48 sliders.

2.2 Experimental Procedure

In every session 10 subjects were told that they would be a "First Mover" and the other 10 that they would be a "Second Mover" for the duration of the session. Each session consisted of 2 practice rounds followed by 10 paying rounds.

In every paying round, each First Mover was paired anonymously with a Second Mover. Each pair's prize was chosen randomly from $\{£0.10, £0.20, ..., £3.90\}$ and revealed to the pair members. The First and Second Movers then completed our slider task sequentially, with the Second Mover discovering the points score of the First Mover she was paired with before starting the task. As explained in Section 2.1, we used a slider task with 48 sliders and an allotted time of 120 seconds. During the task, a number of pieces of information appeared at the top of the subject's screen: the round number; the time remaining; whether the subject was a First or Second Mover; the prize for the round; and the subject's points score in the task so far. If the subject was a Second Mover, she also saw the points score of the First Mover. Figure 2 provides an example of the screen visible to the Second Movers.

The probability of winning the prize for each pair member was 50 plus her own points score minus the other pair member's points score, all divided by 100. Thus, we imposed winning probabilities linear in the difference of the points scores, with equal points scores giving equal winning probabilities, while an increase of 1 in the difference raised the chance of winning by 1 percentage point for the pair member with the higher points score. The probability of winning function was explained verbally and using Table 6 (see Appendix C). At the end of the round, the subjects saw a summary screen showing their own points score, the other pair member's points score, their probability of winning the prize given the respective points scores, the prize for the round and whether they were the winner or loser of the prize in that round.

After each paying round the subjects were re-paired according to Cooper et al. (1996)'s "no contagion" matching algorithm. This rotation-based algorithm ensures that not only do the same subjects never meet each other more than once, but that each round is truly one-shot in the sense that a given subject's actions in one round cannot influence, either directly or indirectly, the actions of other subjects that the subject is paired with later on. The explanation to the subjects in the experimental instructions provides further detail.

Before starting the paying rounds, the subjects played 2 practice rounds to gain familiarity with the task and procedure and to give opportunities for questions. To prevent contamination the subjects were made aware that during the practice rounds they were playing against automata who behaved randomly. At the end of each practice round, the subjects were informed of what their probability of winning would have been given the respective points scores, but were not told that they had won or lost in that round, and no prizes were awarded. We do not include the practice rounds in the econometric analysis.

3 Theoretical Predictions

In this Section we provide a theoretical model of the behavior of a generic pair of First and Second Movers competing for a prize v in a particular round. After describing the model, we show that in the absence of disappointment aversion the Second Mover's effort does not depend on the First Mover's effort, while a disappointment averse Second Mover will respond negatively to the effort choice of the First Mover.

3.1 One-Shot Theory Model

Two agents compete to win a fixed prize of monetary value $v > 0$ in a rank-order tournament, choosing their effort levels sequentially. The First Mover chooses her effort level e_1 from an action space $\mathcal{A} \subseteq [0, \overline{e}]$ which can be discrete or continuous. The Second Mover observes e_1 before choosing her effort level e_2 from $\mathcal{A}$. As noted in Section 2.1, we interpret a subject's points score in the slider task as effort exerted.[5] Agent i's probability of winning the prize $P_i(e_i, e_j)$ increases linearly in the difference between her own effort, e_i, and the other agent's effort, e_j. Assuming symmetry of the probability of winning functions,

$$P_i(e_i, e_j) = \frac{e_i - e_j + \gamma}{2\gamma}, \tag{1}$$

[5]Our use of the term effort therefore corresponds to the behavior of the agent (the number of correctly positioned sliders) rather than the associated cost of positioning the sliders.

where we impose $\gamma \geq \bar{e}$ to ensure that $P_i \in [0,1]$.[6] Throughout we focus on the behavior of the Second Mover conditional on the First Mover's effort e_1. Thus we are able to abstract from any game-theoretic considerations, as the Second Mover faces a pure optimization problem given the First Mover effort that she observes.

3.2 No Disappointment Aversion

Applying the canonical model in the tournament literature, the Second Mover's utility U_2 is separable into utility $u_2(y_2)$ from her tournament payoff $y_2 \in \{0, v\}$, which we call her *material utility*, and her cost of effort $C_2(e_2)$, so

$$U_2(y_2, e_2) = u_2(y_2) - C_2(e_2). \tag{2}$$

This separability assumption in the canonical model is equivalent to saying that: (i) the cost of effort does not depend on whether the agent wins the prize; and (ii) when the monetary prize is awarded, the valuation placed on the prize is independent of how hard the agent worked. The agent exerts effort in a two minute interval before the outcome of the tournament is determined, justifying the first assumption. In relation to (ii), disappointment aversion is a micro-founded explanation of why agents might indeed care about efforts exerted when evaluating the prize (our model of disappointment predicts that the Second Mover's value to winning relative to losing is increasing in her own effort).[7]

Separability implies that the Second Mover's expected utility is given by

$$\begin{aligned} EU_2(e_2, e_1) &= P_2(e_2, e_1)u_2(v) + (1 - P_2(e_2, e_1))u_2(0) - C_2(e_2) \\ &= (u_2(v) - u_2(0)) \left(\frac{e_2 - e_1 + \gamma}{2\gamma} \right) + u_2(0) - C_2(e_2). \end{aligned} \tag{3}$$

As the winning probabilities are linear in the difference in efforts, the First Mover's effort e_1 has no effect on the marginal impact of the Second Mover's effort e_2 on her probability of winning. Thus the Second Mover's marginal utility with respect to her own effort does not depend on e_1, giving the following result.

Proposition 1 *In the canonical model without disappointment aversion the Second Mover's optimal effort e_2^* (or set of optimal efforts) does not depend on the First Mover's effort e_1.*

Note that we have not imposed any concavity, continuity or differentiability assumptions on $u_2(y_2)$ (and nor have we assumed anything about the shape of $C_2(e_2)$). Thus the result continues to hold if the Second Mover exhibits any degree of risk aversion over her monetary payoff, if she places a value on winning per se in addition to the value placed on the monetary payoff from

[6] Che and Gale (2000) call this a piece-wise linear difference-form success function. Note that for any First Mover effort $e_1 \in \mathcal{A}$, the Second Mover's probability of winning function is given by $P_2 = \frac{e_2 - e_1 + \gamma}{2\gamma}$ for the whole range of $e_2 \in \mathcal{A}$ as $e_1 \geq 0$ and $e_2 \leq \bar{e} \leq \gamma$ so $e_2 \leq \gamma + e_1$ and hence $\frac{e_2 - e_1 + \gamma}{2\gamma} \leq 1$, while $e_1 \leq \bar{e} \leq \gamma$ and $e_2 \geq 0$ so $e_2 \geq e_1 - \gamma$ and hence $\frac{e_2 - e_1 + \gamma}{2\gamma} \geq 0$. In our experiment, we set $\bar{e} = 48$ and $\gamma = 50$.

[7] In their related work, Abeler et al. (2009) and Crawford and Meng (2010) make an equivalent separability assumption. In contrast to the standard labor literature where agents vary their hours of work, in our setting the time spent on the task is fixed and therefore only the intensity of effort can affect the valuation of the prize: thus standard complementarities or substitutabilities between leisure and consumption do not apply directly.

winning (as $u_2(v)$ can incorporate this joy of winning), if she is inequity averse over monetary payoffs (Fehr and Schmidt, 1999) or if she is loss averse around a *fixed* reference point (the last two follow as the utility to winning or losing can be redefined to incorporate a comparison to a fixed reference point or to the payoff of the First Mover). The result also holds if $u_2(y_2)$ incorporates an impact of winning or losing on the utility function in any later tournaments, e.g., via changes in wealth or the reference point.

3.3 Disappointment Aversion

Models of disappointment aversion (e.g., Bell, 1985; Loomes and Sugden, 1986; Delquié and Cillo, 2006; Kőszegi and Rabin, 2006, 2007) build on the idea that agents are sensitive to deviations from their expectations, suffering a psychological loss when they receive less than expected and experiencing elation when they receive more. Furthermore, agents anticipate these losses and gains when deciding how to behave.

We follow the literature in embedding disappointment aversion in a loss aversion-type framework. Suppose that the Second Mover compares her material utility $u_2(y_2)$ to a reference level of utility R_2, suffering losses when $u_2(y_2)$ is less than this reference point and enjoying gains when $u_2(y_2)$ exceeds the reference point. Specifically, total utility U_2 is given by[8,9]

$$U_2(y_2, R_2, e_2) = u_2(y_2) + \mathbf{1}_{u_2(y_2)\geq R_2} G_2(u_2(y_2) - R_2) + \mathbf{1}_{u_2(y_2)\leq R_2} L_2(u_2(y_2) - R_2) - C_2(e_2), \quad (4)$$

where the loss function $L_2(x) < 0$ for $x < 0$, the gain function $G_2(x) \geq 0$ for $x > 0$ and $G_2(0) = L_2(0) = 0$. The utility arising from the comparison of $u_2(y_2)$ to the reference point is termed *gain-loss utility*. The Second Mover is said to be *loss averse* if losses due to downward departures from the reference point are more painful than equal-sized upward departures are pleasurable, i.e., $G_2(x) < |L_2(-x)|$ for all $x > 0$. The Second Mover is *first-order loss averse* if she is loss averse in the limit as the deviations from the reference point go to zero, i.e., $\lim_{x\uparrow 0} L_2'(x) > \lim_{x\downarrow 0} G_2'(x)$, assuming differentiability of gain-loss utility except at the kink where $x = 0$.

Starting with Kahneman and Tversky (1979), most models of loss aversion take the reference point to be fixed exogenously, for example assuming it to be equal to the status quo. We noted above that the utility formulation (2) is flexible enough to incorporate loss aversion around a fixed reference point. Thus, a fixed reference point does not introduce any interdependence between the efforts of the First and Second Movers (to see that Proposition 1 continues to hold, note that if $u_2(y_2)$ in (2) is redefined to include gain-loss utility, the analysis proceeds as before).

Instead of holding a fixed reference point, we assume that a disappointment averse Second

[8] Kahneman and Tversky (1979)'s Prospect Theory incorporates a loss averse value function defined only over losses and gains relative to the reference point, while we follow the disappointment aversion literature in defining total utility over both material utility and gain-loss utility arising from the comparison of material utility to the reference point.

[9] By modeling each tournament as a one-shot interaction, we are assuming that our subjects frame each tournament narrowly, i.e., they compare the outcome of each tournament to their reference point in isolation. In our setting, each interaction is one-shot and uncertainty is resolved immediately: at the end of each tournament, the subjects find out whether they won or lost and then get rematched with a new rival. Models and tests of loss aversion generally incorporate narrow framing, either implicitly or explicitly (DellaVigna, 2009) and the literature on narrow framing suggests that attitudes towards small gambles can only be explained by loss aversion together with the narrow framing of individual gambles (Barberis et al., 2006).

Mover is loss averse around an *endogenous* reference point equal to her expected material utility given the effort levels that are actually chosen, so

$$R_2 = E[u_2(y_2)|e_2, e_1]. \tag{5}$$

Thus a Second Mover's reference point will be sensitive to both the effort chosen by the First Mover and her own effort, and when optimizing the Second Mover understands that her effort choice affects her reference point. Notice that the endogeneity of the expectation is crucial. If the Second Mover starts with a reference point equal to a prior expectation which is invariant to the effort levels that are actually chosen, the reference point is fixed so, as explained above, Proposition 1 still holds. Instead, our reference point adjusts to the agents' choices: in the terminology of Kőszegi and Rabin (2007) the reference point is *choice-acclimating*.[10]

To operationalize our model, we linearize material utility and gain-loss utility.[11] We assume that $u_2(y_2) = y_2$, so material utility is linear in money and the Second Mover's reference point becomes her expected monetary payoff, i.e.,

$$R_2 = vP_2(e_2, e_1). \tag{6}$$

Furthermore, we assume that the gain-loss utility arising from the comparison of $u_2(y_2)$ to the reference point is piece-wise linear, with a constant slope of g_2 in the gain domain and l_2 in the loss domain. With piece-wise linearity, loss aversion implies that $l_2 > g_2$, so losses are more painful than same-sized gains are pleasurable.[12] Thus we define disappointment aversion as follows.[13]

Definition 1 *A disappointment averse Second Mover is loss averse around her expected monetary payoff, so* $\lambda_2 \equiv l_2 - g_2$*, which measures the strength of disappointment aversion, is strictly positive.*

[10]Technically our game is psychological as the Second Mover's utility depends on her beliefs about the chosen efforts via the reference point. In particular, our game falls under Battigalli and Dufwenberg (2009)'s framework of a dynamic psychological game as utility depends on terminal node (ex post) beliefs, which are pinned down by the chosen efforts, so beliefs can update during the course of the game.

[11]Given the experimental stakes are small, we believe this comes at a low cost.

[12]With piece-wise linearity, loss aversion and first-order loss aversion are equivalent. If $l_2 = g_2$, gains and losses relative to the reference point cancel out in expectation, so the agent acts as if she had standard preferences.

[13]Our model of disappointment aversion directly extends the single-agent set-up of Bell (1985) to our competitive environment. Our formulation is also equivalent to that of Delquié and Cillo (2006) and the choice-acclimating model of Kőszegi and Rabin (2007, Section IV); it is straightforward to show that in a linear environment with only two outcomes, the reference lottery approach in those papers is equivalent to using a single reference point given by the endogenous expected payoff. We use the same parameterization as Bell (1985) and Delquié and Cillo (2006); Section 4.3.6 explains the equivalence between our parameterization and that used by Kőszegi and Rabin (2007). Although in the same spirit, our model of disappointment is slightly different to that of Loomes and Sugden (1986) who do not allow a kink in utility, but instead use a disappointment/elation function which is non-linear around the endogenous expected payoff. Finally, Kőszegi and Rabin (2006)'s model does not predict a discouragement effect as in their "personal equilibrium" the reference point is taken to be fixed at the point of optimization.

We can then express a disappointment averse Second Mover's expected utility as

$$\begin{aligned} EU_2(e_2, e_1) &= P_2(v + g_2(v - vP_2)) + (1 - P_2)(0 + l_2(0 - vP_2)) - C_2(e_2) \\ &= vP_2 - \lambda_2 v P_2(1 - P_2) - C_2(e_2), \end{aligned} \tag{7}$$

and we let

$$\Lambda_2(e_2, e_1) \equiv -\lambda_2 v P_2(1 - P_2) \tag{8}$$

represent the extra term introduced into expected utility by disappointment aversion. We call Λ_2 the Second Mover's *disappointment deficit* as it is always negative for $\lambda_2 > 0$ (strictly negative for $P_i \notin \{0, 1\}$). For a given prize v the disappointment deficit is proportional to $v^2 P_2(1-P_2)$, the variance of the Second Mover's two-point distribution of monetary payoffs. A disappointment averse Second Mover dislikes variance in her monetary payoff as losses relative to her expected payoff loom larger than gains. (With risk aversion, agents care only about their probability of winning as there are only two possible outcomes.)

The variance is strictly concave in P_2 and maximized at $P_2 = \frac{1}{2}$. When efforts are such that the Second Mover has zero probability of winning, the Second Mover has a reference point of zero and her realized payoff equals her reference point; she is never disappointed and never receives more than expected. Hence her disappointment deficit is zero. Starting at zero, a small increase in her probability of winning leads to a large increase in the variance of her monetary payoff. Further increases in the probability of winning towards $\frac{1}{2}$ lead to further yet smaller increases in the variance. At $P_2 = \frac{1}{2}$ the variance is at its highest so the disappointment deficit is at its most negative - irrespective of whether she wins or loses the Second Mover's realized payoff is very different from her expected payoff. Starting at $P_2 = \frac{1}{2}$ increases in the probability of winning reduce the variance, initially by small amounts, and then by larger amounts as the probability of winning approaches 1.

For any value of the Second Mover's effort, an increase in the First Mover's effort reduces the Second Mover's probability of winning. The variance therefore increases faster in P_2 (when $P_2 < \frac{1}{2}$) or falls less fast in P_2 (when $P_2 > \frac{1}{2}$), so the Second Mover has a lower marginal incentive to exert effort (given her effort always has the same marginal effect on her probability of winning). We thus have a *discouragement effect*, which is crucial to our identification strategy: a disappointment averse Second Mover responds negatively to the First Mover's effort, so the harder the First Mover works the more the Second Mover shies away from exerting effort. Thus First and Second Mover efforts are strategic substitutes.[14]

Proposition 2 *When the Second Mover is disappointment averse, higher First Mover effort discourages the Second Mover: the Second Mover's optimal effort e_2^* is always (weakly) decreasing in the First Mover's effort e_1.*

Proof. See Appendix A.1. ■

Up to now we have imposed no assumptions on the shape of the cost of effort function. In order to derive an analytical expression for how the Second Mover responds to the First Mover's

[14] It is straightforward to extend the proof of Proposition 2 to show that if λ_2 were negative, the Second Mover would respond positively to the First Mover's effort.

effort, and to see how the slope of the reaction function changes in the value of the prize and the strength of disappointment aversion, we now assume a quadratic cost of effort function:

$$C_2(e_2) = be_2 + \frac{ce_2^2}{2}. \tag{9}$$

With this cost function, the Second Mover's objective function will be everywhere convex or everywhere concave. With strict convexity, the Second Mover will always set effort at a corner. Instead we focus here on the case of strict concavity, which allows interior optima, showing that the discouragement effect becomes stronger as the Second Mover becomes more disappointment averse or the value of the prize goes up.

Proposition 3 *Suppose a disappointment averse Second Mover has a quadratic cost function (given by (9)) and a strictly concave objective function, i.e.,* $2\gamma^2 c - \lambda_2 v > 0$*. When the action space is continuous, the slope of the Second Mover's reaction function in the interior is given by*

$$\frac{de_2^*}{de_1} = \frac{-\lambda_2 v}{2\gamma^2 c - \lambda_2 v} < 0 \tag{10}$$

which becomes strictly more negative in the strength of disappointment aversion λ_2 *and the value of the prize* v*. When the action space is discrete, the discrete analogue of the reaction function behaves similarly.*

Proof. See Appendix A.2. ∎

These effects are intuitive. Referring back to (8) we see that the disappointment deficit term becomes more negative in the strength of disappointment aversion λ_2 and the value of the prize v, so the Second Mover becomes more sensitive to First Mover effort as v and λ_2 go up.

4 Empirical Analysis

4.1 Overview and Sample Description

We use the data set collected from the laboratory experiment described in Section 2 to test our theory of disappointment aversion. In Section 4.2 we show in a reduced form setting that, as predicted by our theory of disappointment aversion, Second Movers respond negatively to the effort choice of the First Mover they are paired with and that the strength of this effect is increasing in the value of the prize. In Section 4.3 we use structural modeling to estimate the strength of disappointment aversion on average and the heterogeneity in disappointment aversion across the population. As outlined in the Introduction and Section 2.1, our estimation strategies exploit identifying variation obtained from the properties of our slider task together with the experimental design.[15]

We analyze the behavior of Second Movers conditional on the effort choices of the First Movers. As noted in Section 3.1, this allows us to abstract from any game-theoretic consid-

[15] Evidence from the field, in which agents operate in a natural environment, would complement our laboratory findings. See Levitt and List (2007) for a discussion of the relationship between laboratory and field evidence more generally.

erations as the Second Movers face a pure optimization problem. This conditional analysis is sufficient for the purpose of identifying the presence and strength of disappointment aversion. Moreover, solving for the optimal behavior of the First Movers would require further assumptions concerning the First Movers' beliefs about the unobserved characteristics and behavior of the Second Movers. We avoid these issues, together with the associated computational complexities and potential sources of misspecification, when performing a conditional analysis of the Second Mover effort choices.[16]

As explained in Section 2.1, we interpret the number of sliders correctly positioned by a subject within the allotted time, i.e., the points score, as the effort exerted by the subject in the task. While the slider task provides a finely gradated measure of effort, effort is still discrete. We emphasize that this discreteness is entirely unproblematic. Indeed, the above theoretical framework encompasses both discrete and continuous effort choices, and the testable implications of our theory of disappointment aversion apply irrespective of whether effort is discrete or continuous. In addition, as detailed below, discrete effort choices are easily accommodated in our structural model.

Paying Round	Mean(e_1)	SD(e_1)	Mean(e_2)	SD(e_2)	Minimum		Maximum	
					e_1	e_2	e_1	e_2
1	22.034	5.991	21.763	6.101	1	0	33	34
2	22.627	6.708	23.458	4.836	0	11	33	33
3	24.763	6.075	24.831	4.875	0	12	37	38
4	24.627	5.956	25.203	4.502	0	16	35	36
5	24.966	6.800	25.119	5.660	0	0	36	35
6	24.729	7.508	24.898	7.039	1	0	37	39
7	25.881	5.855	25.763	6.109	9	0	37	37
8	26.831	5.858	26.169	5.133	9	14	41	35
9	25.593	8.550	26.254	6.702	0	0	38	40
10	26.322	6.781	26.729	5.988	1	0	40	39

Notes: SD denotes standard deviation and e_1 and e_2 denote, respectively, First and Second Mover effort.

Table 1: Summary of First and Second Mover efforts.

From the laboratory sessions we collected data on 60 First Movers and 60 Second Movers, each observed for 10 paying rounds, with re-pairing between rounds as detailed in Section 2.2. One Second Mover appears to have been unable to position any sliders at exactly 50.[17] Throughout our analysis this subject is dropped, except for the purpose of showing that our results are robust to our sample selection. Table 1 summarizes the behavior of the 59 Second Movers and the corresponding First Movers in each round. Efforts range between 0 and 41 sliders for First

[16]Similar problems would arise if we attempted to identify disappointment aversion from responses to the prize in a simultaneous-move tournament. Furthermore, in a simultaneous-move context, even if all subjects were identical disappointment aversion would be difficult to identify as symmetric and asymmetric pure-strategy equilibria co-exist for certain values of the prize and subjects might play mixed-strategy equilibria.

[17]The data show that this subject was moving sliders around throughout the session but failed to position any sliders at exactly 50 in either the practice rounds or in the paying rounds. This subject also experienced problems when entering his/her Participant ID number.

Movers and 0 and 40 sliders for Second Movers. Within each round, on average First and Second Movers exert roughly the same effort, with average effort increasing from around 22 sliders to just under 27 sliders over the 10 rounds.

4.2 Reduced Form Analysis

We use a panel data regression to examine whether Second Movers respond to the effort choice of the First Mover they are paired with. Exploiting Proposition 1, we hypothesize that if Second Movers are not disappointment averse then the observed efforts of the Second Movers will not depend on the corresponding First Mover efforts once controls for the prize and round effects are included.[18] Alternatively, if subjects are disappointment averse then Proposition 2 implies a negative dependence of observed Second Mover efforts on the corresponding First Mover efforts, again conditional on controls for the prize and round effects.

To explore how Second Movers respond to First Mover effort we estimate the following linear random effects panel data model:

$$e_{2,n,r} = \beta_1 + \beta_2 v_{n,r} + \beta_3 e_{1,n,r} + \beta_4 e_{1,n,r} \times v_{n,r} + d_r + \omega_n + \epsilon_{n,r} \quad \text{for } n = 1, \ldots, N; \; r = 1, ..., 10, \quad (11)$$

where n and r index, respectively, Second Movers and paying rounds, and N denotes the total number of Second Movers. $e_{1,n,r}$ is the effort of the First Mover paired with the n^{th} Second Mover in the r^{th} round, and $v_{n,r}$ is the prize draw for the n^{th} Second Mover in the r^{th} round. The prize, the First Mover's effort and the First Mover's effort interacted with the prize are included as explanatory variables. The inclusion of the interaction of the prize and the First Mover's effort is motivated by Proposition 3 which shows that in the case of a quadratic cost of effort function the negative effect of the First Mover's effort on the Second Mover's optimal effort is larger at higher prizes. Additionally, the equation includes a set of round dummies denoted by d_r for $r = 1, ..., 10$, with the first paying round providing the omitted category, to capture systematic differences between rounds which are common across Second Movers, and round invariant Second Mover specific effects denoted ω_n for $n = 1, \ldots, N$ to capture systematic differences between Second Movers. Lastly, $\epsilon_{n,r}$ is an unobservable that varies over rounds and over Second Movers and captures differences between rounds in a Second Mover's effort choice that cannot be attributed to the other terms in the model. ω_n is assumed to be identically and independently distributed over Second Movers with a variance σ^2_ω, while $\epsilon_{n,r}$ is assumed to be identically and independently distributed over rounds and Second Movers with a variance σ^2_ϵ.

Table 2 reports estimates of the parameters appearing in (11). The results for the preferred sample show a negative effect of First Mover effort on Second Mover effort. In more detail, at low prizes First Mover effort does not significantly affect Second Mover effort, while at high prizes there is a large and significant discouragement effect as predicted by our theory of disappointment aversion. Application of the Delta method reveals that the effect of First Mover effort on Second Mover effort is not significant at the 5% level for prizes less than £2, is significant at the 5% level for prizes between £2 and £2.60, and is significant at the 1% level for prizes of £2.70 and above. For the highest prize of £3.90 a 40 slider increase in First Mover effort decreases

[18]We note however that First and Second Mover efforts will not be unconditionally independent in the presence of prize and round effects which impact on both pair members.

Second Mover effort by approximately 6 sliders, a 24% decrease relative to the average effort of 25 sliders.[19] Furthermore, there is a large and significant positive prize effect, and we find that the persistent unobserved individual characteristics explain more of the variation in behavior than the transitory unobservables.[20]

	Preferred Sample 59 Second Movers		Full Sample 60 Second Movers	
	Coefficient	Standard Error	Coefficient	Standard Error
First Mover effort	0.044	0.049	0.047	0.049
Prize	1.639***	0.602	1.655***	0.592
Prize×First Mover effort	−0.049**	0.023	−0.050**	0.023
Intercept	19.777***	1.400	19.392***	1.447
σ_ω	4.288		5.342	
σ_ϵ	3.852		3.826	
$N \times R$	590		600	
Hausman test for random versus fixed effects	2.60 $df = 12, p = 0.998$		2.43 $df = 12, p = 0.998$	

Notes: *, ** and *** denote significance at the 10%, 5% and 1% levels. *df* denotes degrees of freedom. Both specifications further include dummy variables for each of rounds 2-10 inclusive. The coefficients on these variables are between 1.7 and 5.2, significantly greater than zero, and tend to increase over the rounds.

Table 2: Random effects regressions for Second Mover effort.

We note that, although the parameters reported in Table 2 were estimated from a linear random effects model, an alternative specification in which round invariant Second Mover specific effects are treated as fixed effects yields almost indistinguishable results. This is because Second Mover specific effects are uncorrelated with the prize and the First Mover efforts due to the experimental design. Finally, Table 2 shows that including the 60^{th} Second Mover does not change conclusions concerning significance, and nor does this have substantial effects on the coefficient estimates.

4.3 Structural Modeling

Structural modeling seeks to fit the theoretical model with disappointment aversion presented above in Section 3.3 to the experimental sample. In contrast to the reduced form analysis above, structural modeling recovers estimates of the strength of disappointment aversion on average and the population-level heterogeneity in disappointment aversion. Below we describe our preferred

[19]We use a 40 slider increase as an illustrative example as First Mover efforts ranged from 0 to about 40 (see Table 1).

[20]To test whether behavior changes during the course of the experiment due to learning about the payoff function, we also estimated the model with separate coefficients on First Mover effort and First Mover effort interacted with the prize for the first five rounds of the experiment and for the final five rounds. The parameters corresponding to the first half of the experiment are not statistically significantly different from those corresponding to the second half (p value of 0.710). We further estimated the model excluding all prize controls, and found a negative but statistically insignificant effect of First Mover effort on Second Mover effort: both First and Second Mover efforts are positively correlated with the prize, so without prize controls the coefficient on First Mover effort is biased upward as it picks up part of the effect of the prize on Second Mover effort.

empirical specification, our estimation strategy, including a discussion of identification, and our results. We then proceed to explore robustness to the specification of the reference point and of the cost of effort function. Finally, we relate our estimate of the disappointment aversion parameter to existing measures of loss aversion around fixed reference points.

4.3.1 Preferred Empirical Specification

We use $\lambda_{2,n}$ to denote the disappointment aversion parameter of the n^{th} Second Mover. In this specification the strength of disappointment aversion may vary between subjects; however, for a given subject the strength of disappointment is constant over rounds. We adopt the following specification for $\lambda_{2,n}$:

$$\lambda_{2,n} \sim N(\widetilde{\lambda}_2, \sigma_\lambda^2) \quad \text{for} \quad n = 1, \ldots, N, \tag{12}$$

and further assume that $\lambda_{2,n}$ is independent over Second Movers. The parameter $\widetilde{\lambda}_2$ represents the strength of disappointment aversion on average, and σ_λ^2 denotes the variance of the strength of disappointment aversion in the population.

The cost of effort function is assumed to be quadratic, as in (9). The parameter b is assumed to be constant over rounds and common to Second Movers, while unobserved cost differences between Second Movers and learning effects enter the cost of effort function through the convexity parameter c. $c_{n,r}$ denotes the convexity parameter of the n^{th} Second Mover in the r^{th} round and takes the following form:

$$c_{n,r} = \kappa + \delta_r + \mu_n + \pi_{n,r} \quad \text{for} \quad n = 1, \ldots, N; \; r = 1, ..., 10. \tag{13}$$

In the above κ denotes the component of $c_{n,r}$ which is common across Second Movers and rounds. δ_r for $r = 1, ..., 10$ are round effects, with the first paying round providing the omitted category. These round dummies allow the marginal costs of the first and later units of effort to vary over rounds at the population level. A cost of effort that is declining over rounds due to learning is represented by values of δ_r which are negative and decreasing over rounds. μ_n denotes unobserved differences in the cost of effort functions across Second Movers that are constant over rounds. For the purpose of estimation μ_n is assumed to be independent over Second Movers and to have a Weibull distribution with scale parameter ϕ_μ and shape parameter φ_μ. The final term in the cost function is $\pi_{n,r}$ which represents unobserved differences in Second Movers' cost of effort functions that vary over rounds as well as over Second Movers. $\pi_{n,r}$ is assumed to be independent over Second Movers and rounds and to have a Weibull distribution with scale parameter ϕ_π and shape parameter φ_π. The Weibull distribution is a flexible two parameter distribution that has positive support, thus allowing us to impose convex cost of effort functions on all Second Movers when estimating the model.

Given this parameterization of the theoretical model, the structural model has 17 unknown parameters, corresponding to the parameters describing disappointment aversion, $\widetilde{\lambda}_2$ and σ_λ, the common cost parameters b and κ, the 9 round effects δ_r for $r = 2, ..., 10$ and the 4 parameters appearing in the distribution of the unobservables in the cost of effort function, namely, ϕ_μ, φ_μ, ϕ_π and φ_π. These 17 structural parameters are collectively denoted by the vector θ.

4.3.2 Estimation Strategy and Identification

We estimate the 17 unknown parameters using the Method of Simulated Moments (MSM) (McFadden, 1989; Pakes and Pollard, 1989). The analytic complexity of choice probabilities, due to the multiple sources of unobserved heterogeneity, precludes the use of Maximum Likelihood and Method of Moments estimation techniques. MSM, in contrast, uses easily computed features of the sample as the basis for estimating the unknown parameters. Formally, the sample observations are used to compute a $k \times 1$ dimensional vector of moments, with $k \geq 17$, denoted M. Critically, every moment included in M should depend at least in part on one or more endogenous variables. The researcher has considerable discretion over the moments included in M; however M typically includes period specific averages of endogenous variables, here the effort choices of the Second Movers in each round, together with correlations between the endogenous variables and the explanatory variables.

MSM proceeds by generating S simulated samples. Each simulated sample contains N Second Movers each observed for 10 rounds. In each simulated sample the Second Movers face the same prizes and First Mover efforts as observed in the actual sample. The behavior of the Second Movers in the simulated samples is determined from the structural model using a trial value, θ_t, of the values of the unknown parameters, θ. In particular, unobservables are assigned to Second Movers in accordance with the above described distributions. For each Second Mover and each round, the expected utility is calculated for each feasible Second Mover effort choice, and the simulated effort choice is the action with the highest expected utility. Further details concerning the construction of the simulated samples are provided in Appendix B.1.

The behavior of the Second Movers in the simulated samples is then compared to the behavior of the actual experimental subjects. Specifically, for each of the S simulated samples the vector of moments $M_s(\theta_t)$ is computed. These are the same k moments as computed for the observed sample. The simulated moments M_s are a function of the parameters θ_t used to simulate the behavior of the Second Movers as different values of the parameters imply different optimal Second Mover effort choices. The average of M_s over the S simulated samples, $\frac{1}{S}\sum_{s=1}^{S} M_s(\theta_t)$, provides a summary of the behavior of Second Movers in the simulated samples. The process of averaging over the S simulated samples reduces the effect of simulation noise on the simulated moments. The following metric is then formed:

$$J(\theta_t) = \left(M - \frac{1}{S}\sum_{s=1}^{S} M_s(\theta_t) \right)' W_N \left(M - \frac{1}{S}\sum_{s=1}^{S} M_s(\theta_t) \right), \tag{14}$$

where W_N is a fixed $k \times k$ dimensional positive semidefinite weighting matrix. The quantity $J(\theta_t)$ provides a scalar measure of the distance between the observed behavior of the actual experimental subjects and the behavior of the Second Movers in the simulated samples at the trial parameter vector θ_t. The MSM estimator of θ, denoted $\widehat{\theta}$, is the value of θ_t that minimizes $J(\theta_t)$: $\widehat{\theta} = \text{argmin}_{\theta_t} J(\theta_t)$. Thus MSM estimates the structural parameters to be such that the behavior of Second Movers simulated on the basis of the structural model is as similar as possible to the behavior of the actual Second Movers as observed in sample.

Under the conditions of Pakes and Pollard (1989), the MSM estimator is consistent and asymptotically normal for any consistent weight matrix W_N. We use a weight matrix with diagonal elements equal to the inverse of N times the variances of the sample moments and zeros elsewhere and use bootstrap sampling of Second Movers with replacement to estimate W_N.[21] Further details pertaining to the properties of the MSM estimator and estimation routine are presented in Appendix B.2.

We use 38 moments to estimate the 17 structural parameters. The moments are described in Table 4 in Appendix B.3. Correlations between Second Mover effort and First Mover effort and between Second Mover effort and First Mover effort interacted with the prize provide identifying information about $\widetilde{\lambda}_2$, the parameter describing the strength of disappointment aversion on average. Percentiles of Second Mover specific correlations provide information about the standard deviation of disappointment aversion in the population, σ_λ. The correlation between Second Mover effort and the prize helps to identify κ, which measures the component of the convexity of the cost of effort function common to Second Movers and rounds, while the associated percentiles help to identify the shape of the distributions of the unobserved cost differences between Second Movers. Moments pertaining to the marginal distribution of Second Mover effort, such as round specific means and the standard deviation, provide further identifying information.

4.3.3 Results

The upper left panel of Table 3 reports the parameter estimates for the preferred specification. Before discussing the results we briefly consider the goodness of fit of the preferred specification, presented in Table 5 located in Appendix B.3. Table 5 shows that all fitted moments correspond closely to the values observed in the sample: in particular the z test statistics show that the observed and fitted moments never differ by more than 1.2 bootstrapped standard deviations. Consistent with this, the Newey test for the validity of overidentifying restrictions (OI test), reported in Table 3, does not reject the validity of the preferred specification.

Turning to the parameter estimates for the preferred specification, our estimate of the strength of disappointment aversion on average, $\widetilde{\lambda}_2$, is 1.729 and this is significantly different from zero at all conventional significance levels.[22] In Section 4.3.6 we place this estimate in the context of the related literature but we note here that a figure of 1.729 is in line with previous studies which estimate the strength of loss aversion around a fixed reference point. We find that σ_λ is significantly greater than zero, thus providing evidence for heterogeneity in disappointment aversion across individuals. Our parameter estimates imply that $\lambda_{2,n}$ is greater than 3.3 for 20% of individuals, and is less than 0.2 for 20%. For 17% of individuals, $\lambda_{2,n}$ is less than zero.

[21] Using instead the optimally weighed minimum distance estimator improves efficiency but can introduce considerable finite sample bias (see Altonji and Segal, 1996).

[22] We follow most of the literature in using the term “disappointment aversion” to describe this kink in utility around a choice-acclimating expectations-based reference point; we note, however, that our empirical results provide no direct evidence about the psychological processes which might underlie the kink.

	Preferred Specification		Non-Quadratic Cost of Effort		Normally Distributed Cost Unobservables	
	Estimate	SE	Estimate	SE	Estimate	SE
$\widetilde{\lambda}_2$	1.729***	0.532	1.758***	0.640	1.260***	0.470
σ_λ	1.823***	0.556	1.868***	0.634	1.393***	0.481
b	-0.538***	0.036	-0.407***	0.018	-0.493***	0.012
κ	1.946***	0.103	2.063***	0.135	2.427***	0.059
σ_μ	0.516***	0.062	0.902***	0.151	0.266***	0.024
σ_π	0.346***	0.127	0.716***	0.204	0.204***	0.030
α	-	-	-	-	-	-
ψ	-	-	2.534***	0.128	-	-
$de_2/de_1(v$=£0.10, low $\lambda_{2,n})$	-0.000	0.001	-0.000	0.001	-0.000	0.002
$de_2/de_1(v$=£2, average $\lambda_{2,n})$	-0.030***	0.011	-0.028**	0.013	-0.025*	0.013
$de_2/de_1(v$=£3.90, high $\lambda_{2,n})$	-0.127***	0.026	-0.107***	0.034	-0.100***	0.019
OI test	25.555 [0.224]		13.435 [0.858]		61.480 [0.000]	

	Own-Choice-Acclimating Reference Point ($g_2 = 0$)		Own-Choice-Acclimating Reference Point ($g_2 = 1$)		Full Sample: 60 Second Movers	
	Estimate	SE	Estimate	SE	Estimate	SE
$\widetilde{\lambda}_2$	2.070***	0.426	1.909***	0.664	1.200***	0.426
σ_λ	1.476**	0.643	1.201**	0.534	1.206*	0.654
b	-0.615***	0.017	-0.591***	0.015	-0.486***	0.024
κ	2.187***	0.103	2.102***	0.060	1.769***	0.071
σ_μ	0.526***	0.050	0.578***	0.077	0.600***	0.110
σ_π	0.410***	0.086	0.345***	0.062	0.317***	0.122
α	0.944***	0.236	0.986***	0.156	-	-
ψ	-	-	-	-	-	-
$de_2/de_1(v$=£0.10, low $\lambda_{2,n})$	-0.001	0.001	-0.001	0.001	-0.000	0.001
$de_2/de_1(v$=£2, average $\lambda_{2,n})$	-0.034***	0.012	-0.032***	0.012	-0.024**	0.011
$de_2/de_1(v$=£3.90, high $\lambda_{2,n})$	-0.106***	0.027	-0.099***	0.026	-0.096***	0.028
OI test	11.583 [0.930]		20.980 [0.398]		24.005 [0.293]	

Note 1: *, ** and *** denote significance at the 10%, 5% and 1% levels. Where applicable, standard deviations of the transitory and persistent unobservables in the cost of effort function, σ_π and σ_μ, are computed from the estimates of the parameters of the Weibull distribution. Estimates of κ, σ_π and σ_μ have been multiplied by 100.

Note 2: All specifications further include dummy variables for each of rounds 2-10 inclusive. In the preferred specification, the coefficients on these variables, scaled as per κ, are between -0.1 and -0.5, significantly less than zero, and tend to decrease over the rounds.

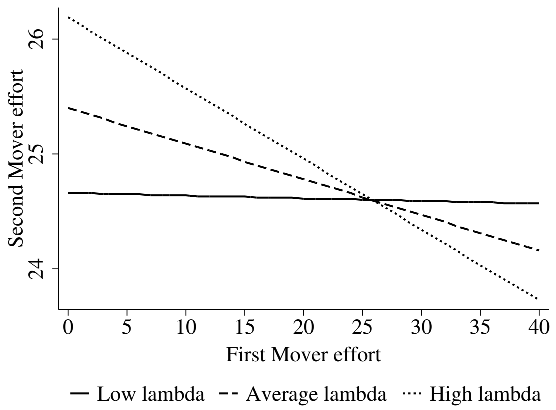
Note 3: Reaction functions and their gradients were obtained using simulation methods. Using the estimated parameters of the cost of effort function for round 5, we simulated a large number of hypothetical Second Mover optimal efforts conditional on specific values of First Mover effort and the prize, and computed the mean best response. The reaction functions are linear, except in the case of non-quadratic effort costs where we evaluate the gradients at $e_1 = 20$. Low, average and high $\lambda_{2,n}$ refer to the 20^{th}, 50^{th} and 80^{th} percentiles of the distribution of $\lambda_{2,n}$.

Note 4: The construction of the test statistic for the validity of overidentifying restrictions (OI test) is detailed in Newey (1985). p values are shown in brackets.

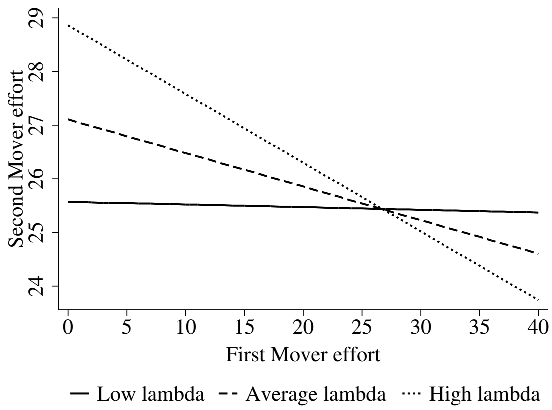
Note 5: Unless stated otherwise, all results were obtained using our preferred sample of 59 Second Movers.

Table 3: MSM parameter estimates.

The results further show that the cost of effort function exhibits significant convexity. In addition there is significant transitory and permanent variation over Second Movers in the cost of effort, with persistent unobserved differences being more important than transitory differences.[23] Our estimate of b, the linear component of the cost of effort function, is negative, indicating that the cost of effort is declining at low effort levels. This negative coefficient is required to fit accurately observed average Second Mover effort. However, the linear component of the cost of effort function does not affect how Second Movers respond to the First Movers' efforts. Moreover, it is not surprising that the cost of effort is at first declining as the experimental subjects have self-selected into participating in the experiment and the outside option during the task is to do nothing for 120 seconds. Other experiments have also found that subjects derive some utility from carrying out real effort tasks, e.g., Brüggen and Strobel (2007).



(a) Prize=£2.



(b) Prize=£3.90.

Notes: We illustrate the reaction functions over the range 0 to 40 sliders as Table 1 shows First Mover efforts varied over this range. Note 3 to Table 3 explains how these reaction functions are constructed. Error bars are omitted; standard errors for the average $\lambda_{2,n}$ case in subfigure (a) and for the high $\lambda_{2,n}$ case in subfigure (b) are reported in Table 3. Low, average and high $\lambda_{2,n}$ refer to the 20$^{\text{th}}$, 50$^{\text{th}}$ and 80$^{\text{th}}$ percentiles of the distribution of $\lambda_{2,n}$.

Figure 3: Reaction functions implied by the preferred specification of the structural model.

Figure 3 shows the extent to which heterogeneity in disappointment aversion translates into differences in mean Second Mover responses to First Mover effort, evaluated at the average prize of £2 and at the highest prize of £3.90. Second Movers with low values of $\lambda_{2,n}$, defined to be the 20$^{\text{th}}$ percentile of the distribution of $\lambda_{2,n}$, do not respond appreciably to changes in First Mover effort. In contrast, we observe a significant discouragement effect (at the 1% level) for Second Movers with average values of $\lambda_{2,n}$, or with high values, defined to be the 80$^{\text{th}}$ percentile of the distribution of $\lambda_{2,n}$. At the highest prize of £3.90, a 40 slider increase in First Mover effort decreases optimal Second Mover effort by 2.5 sliders for an individual with the average $\lambda_{2,n}$, and by 5.1 sliders for an individual with a high $\lambda_{2,n}$. In the context of an average Second Mover effort of 25, these effects represent reductions of 10% and 20% respectively in optimal

[23]The magnitude and significance of the parameters controlling the persistent unobservables are indicative of the importance of our assumptions about persistent unobserved heterogeneity; to confirm their importance, we also estimated a simpler model (parameter estimates not reported) in which all unobserved heterogeneity comes through a mean zero normally distributed error term, assumed to be independent over both rounds and subjects, and found that the Newey test rejects this specification (p value of 0.000).

Second Mover effort.[24]

4.3.4 Robustness: Own-Choice-Acclimating Reference Point

The expectations-based reference point in our model adjusts to both the First Mover's and the Second Mover's effort choices. Thus our finding of significant disappointment aversion provides evidence of loss aversion around choice-acclimating reference points when agents compete.

With a fixed reference point, including one given by a prior expectation, Proposition 1 shows that we should observe no discouragement effect. However, if the expectations-based reference point adjusted only to the First Mover's effort, there would still exist a discouragement effect.[25] In order to test whether the expectations-based reference point adjusts only to the First Mover's effort, we generalize the reference point (6) as follows for $\alpha \in [0, 1]$:

$$R_2 = \alpha v P_2(e_2, e_1) + (1 - \alpha) v P_2(\widetilde{e}_2, e_1), \tag{15}$$

where $\widetilde{e}_2$ is fixed, and so does not adjust to the Second Mover's choice of effort ($\widetilde{e}_2$ could for instance arise from a prior expectation).

We re-estimate our model, simultaneously estimating α as well as the 17 other parameters from the preferred specification.[26] The bottom lower and bottom middle panels of Table 3 show that we estimate α to be close to 1, so the Second Movers place little weight on the part of the reference point that does not adjust to their own effort choice. Moreover, the estimates of α are significantly different from zero at the 1% level. We argue that this provides strong evidence that the Second Movers' reference points are indeed own-choice-acclimatizing, as assumed in the preferred specification.

4.3.5 Further Robustness

The remaining panels in Table 3 provide further robustness checks for various features of our analysis. The upper middle panel of Table 3 reports the results for a specification in which the cost of effort function is not constrained to be quadratic, but instead takes the form $C(e_2) = be_2 + \frac{ce_2^{\psi}}{\psi}$, where ψ is an additional parameter to be estimated. We estimate ψ to be approximately 2.5.[27] In the upper right panel, we report estimates of a specification in which the unobservables

[24] The magnitudes of the estimated slopes are somewhat lower than the corresponding estimates implied by the reduced form analysis in Section 4.2. This is because MSM seeks to fit simultaneously a variety of different moments. If we arbitrarily put a higher weight on the moments identifying these slopes, the estimated magnitudes would be larger.

[25] Similarly, in Abeler et al. (2009) the main empirical findings are consistent with a reference point which adjusts to the fixed payment but not the subjects' effort choices.

[26] With this more general reference point, the fixed $\widetilde{e}_2$ and the slope of gain-loss utility in the gain domain, g_2, become relevant to the determination of the level of effort (but not to how the Second Movers respond to First Mover effort). As g_2 and $\widetilde{e}_2$ are not identified under the null that $\alpha = 1$, we do not attempt to estimate these parameters, instead estimating the model for various values of g_2 and $\widetilde{e}_2$. Results for $g_2 = 0$ and $g_2 = 1$ with $\widetilde{e}_2$ equal to the average level of effort of 25 are reported in Table 3. We further estimated the model with $g_2 = \frac{1}{2}$, and also with $\widetilde{e}_2 = 0$ together with different values of g_2. The results were not substantially different.

[27] At the estimated parameters of this specification, the qualitative predictions of Proposition 3 continue to hold numerically. For every possible First Mover effort, the simulated Second Mover reaction function evaluated at the average $\lambda_{2,n}$ becomes steeper as the prize moves from £0.10 to £2 and from £2 to £3.90. Similarly, at the average prize of £2, the reaction function becomes steeper as we move from low $\lambda_{2,n}$ to the average $\lambda_{2,n}$ and from the average $\lambda_{2,n}$ to high $\lambda_{2,n}$. Note 3 to Table 3 details the construction of these reaction functions.

appearing in the cost of effort function are normally distributed, rather than being drawn from Weibull distributions. The Newey test for the validity of overidentifying restrictions (OI test) rejects this specification, which illustrates the flexibility of the Weibull distribution. Finally, the bottom right panel shows results obtained for the preferred specification but estimated with the full sample of 60 Second Movers (see Footnote 17 for details concerning the omitted Second Mover).

We see that irrespective of the choice of sample and the specification of the cost of effort function our estimate of the strength of disappointment aversion on average $\widetilde{\lambda}_2$ is significantly different from zero. Also, all specifications show significant variation across individuals in the strength of disappointment aversion. Finally, the estimated response of a Second Mover to a change in First Mover effort varies little across specifications.

4.3.6 Relationship to Existing Estimates of Loss Aversion

The endogeneity of the reference point means that behavior in our model is driven by the size of the kink in gain-loss utility $\lambda_2 = l_2 - g_2$. Other models of choice-acclimating reference points share the same feature. To see this, we introduce Kőszegi and Rabin (2006, 2007)'s parameterization, which involves a weighting on gain-loss utility relative to material utility, $\eta \geq 0$, and a coefficient of loss aversion for gain-loss utility, λ, which measures the ratio of the slopes of gain-loss utility alone in the loss and gain domains. We estimate the size of the kink in gain-loss utility, scaled relative to material utility, and $\lambda_2 = \eta\lambda - \eta = \eta(\lambda - 1)$. In their model of single-agent effort provision, Abeler et al. (2009)'s first-order conditions also depend on $\eta(\lambda-1)$, as do preferences over lotteries in the choice-acclimating version of Kőszegi and Rabin (2007)'s model (see p. 1059 and Proposition 12(i)). Bell (1985)'s original disappointment aversion model also builds on the size of the kink. We cannot estimate λ directly, as this coefficient interacts with the weight put on gain-loss utility to determine the size of the kink in gain-loss utility; nonetheless, because we estimate that $\widetilde{\lambda}_2 > 0$, it follows that $\eta > 0$ and $\lambda > 1$.

Our measure of disappointment aversion is therefore not directly comparable to previous measures of loss aversion around fixed reference points. Evidence from previous studies suggests a coefficient of loss aversion of about 2 for Kahneman and Tversky (1979)'s value function (Kahneman, 2003), i.e., the value function is about twice as steep in the loss domain as it is in the gain domain. For example, from choices over lotteries Tversky and Kahneman (1992) estimate a coefficient of 2.25 for their median subject. Kahneman and Tversky (1979)'s value function is defined only over gains and losses: if we consider this value function to include implicitly any consumption value of losses and gains as well as psychological elation and pain from deviating from the reference point, then the comparable figure in our setting to the usual loss aversion coefficient is the ratio of the slopes of total utility in the loss and gain domains, given by

$$\frac{1 + l_2}{1 + g_2} = 1 + \frac{\lambda_2}{1 + g_2}. \tag{16}$$

Given an assumption about g_2, our estimate of $\widetilde{\lambda}_2$ therefore implies an estimate of the average value of (16) in the population. For example, if we assume that $g_2 \in (0, 1)$, so the elation associated with receiving more than expected is positive but less important than the associated material utility, then our estimate $\widetilde{\lambda}_2 = 1.729$ implies that (16) $\in (1.865, 2.729)$, which matches previous estimates of the coefficient of loss aversion.

5 Alternative Behavioral Explanations

Our model of disappointment aversion fits our data well: as explained in Section 4.3.3, all fitted moments correspond closely to the values observed in our experimental sample and the Newey test shows that our preferred specification is not rejected by the data. This is good statistical evidence that there are not important additional factors which would help to explain our data better. Furthermore, the burgeoning empirical literature which shows the importance of expectations-based reference points in many different contexts (summarized in the Introduction) lends weight to our thesis that expectations might be salient when agents compete. Nonetheless, we argue below that a number of alternative behavioral explanations of the observed discouragement effect are unconvincing.

Peer effects. Second Movers who imitate the behavior of their peers (Falk and Ichino, 2006), or who compete by matching or beating their rival's effort level, would respond positively rather than negatively to the effort of the First Mover they are paired with. Moreover, we find no evidence of matching or beating. Specifically, if Second Movers have a tendency to match their rival's effort we should see few Second Movers completing one slider fewer or one slider more than their rival. Similarly, if Second Movers tend to want to beat their rival's effort we should see few Second Movers completing the same number of sliders or two sliders more than their rival. Formal tests of these hypotheses reveal no significant evidence of either matching or beating behavior.[28]

Probability weighting. Kahneman and Tversky (1979) propose that agents apply decision weights to probabilities, overweighting small probabilities and underweighting large ones. The evidence further suggests that the probability weighting function $w(P)$ is concave for probabilities smaller than about 35% to 40% and convex thereafter (Wu and Gonzalez, 1996; Prelec, 1998). A Second Mover who evaluated the prospect arising from her choice of effort using probability weighting would show a discouragement effect in the convex region to the right of the inflection point, but an opposite *encouragement effect* in the concave region to the left of the inflection point.[29] To test for such a pattern, we estimate the reduced form model from Section 4.2 with separate coefficients on First Mover effort and First Mover effort interacted with the prize for the highest 50% of First Mover efforts (which, on average, give rise to low Second Mover winning probabilities) and for the lowest 50% of First Mover efforts (which tend to give

[28] In more detail, let $\mathbf{Pr}(x) \equiv \frac{\sum_{n=1}^{59}\sum_{r=1}^{10}\mathbf{1}_{e_{2,n,r}-e_{1,n,r}=x}}{590}$ be the proportion of Second Mover efforts for which the difference between the Second Mover's effort and that of the First Mover she is paired with is exactly x. To test for matching behavior we conduct two joint non-parametric bootstrapped tests. Our first test cannot reject the null that $\mathbf{Pr}(-1) = \mathbf{Pr}(-2)$ and $\mathbf{Pr}(-1) = \mathbf{Pr}(0)$, and the second cannot reject the null that $\mathbf{Pr}(1) = \mathbf{Pr}(0)$ and $\mathbf{Pr}(1) = \mathbf{Pr}(2)$, where in each case the one-sided alternative is that the middle proportion is significantly lower than either of the proportions above or below (or lower than both). The p values are, respectively, 0.481 and 0.937. Similarly, when testing for beating behavior, our first test cannot reject the null that $\mathbf{Pr}(0) = \mathbf{Pr}(-1)$ and $\mathbf{Pr}(0) = \mathbf{Pr}(1)$, and the second cannot reject the null that $\mathbf{Pr}(2) = \mathbf{Pr}(1)$ and $\mathbf{Pr}(2) = \mathbf{Pr}(3)$. The p values are, respectively, 0.832 and 0.138.

[29] The prospect arising from an effort choice e_2 is "simple" (one non-zero outcome) and, with $u_2(0) = 0$, is valued at $w(P_2)u_2(v)$ (see Prelec, 1998, p. 500). Given $\frac{\partial P_2}{\partial e_2} = -\frac{\partial P_2}{\partial e_1} = \frac{1}{2\gamma} > 0$, $\frac{\partial w}{\partial P_2}\frac{\partial P_2}{\partial e_2}u_2(v)$ is increasing (decreasing) in e_1 when $w(P_2)$ is concave (convex) in P_2, so the Second Mover's marginal incentive to exert effort rises (falls) locally in e_1 for a given e_2.

rise to higher Second Mover winning probabilities). The parameter estimates are of similar magnitude and have the same signs as those estimated in Section 4.2; furthermore, the parameters corresponding to the lower half of First Mover efforts are not statistically significantly different from those corresponding to the upper half (p value of 0.830).[30] This provides evidence that, in contrast to the pattern predicted by probability weighting, the discouragement effect that we observe in the data operates throughout the range of Second Mover winning probabilities.

Regret. It is not straightforward to introduce a notion of regret (Bell, 1982; Loomes and Sugden, 1982) into our set-up as the agents have more than two possible choices and uncertainty about the outcome of alternative choices is only partially resolved ex post (Bell, 1983, discusses partial resolution of uncertainty in a two action model). Furthermore we believe that, because our subjects have only limited potential to learn what would have happened in the counterfactual in which they chose a different level of effort, regret will not be particularly salient in the context of our experiment; as Larrick (1993, p. 446) puts it: "expecting vivid, concrete feedback about what definitely would have occurred produces a greater potential for regret than pallid, abstract knowledge of what statistically was likely to occur." Nonetheless, we estimate a structural model including regret instead of disappointment to see whether regret can help to explain the behavior in our experiment. We assume that regret is felt when the realized payoff $u_2(y_2) - C_2(e_2)$ is less than the ex post expected payoff from the ex post best alternative action.[31] We find that the parameter measuring the average intensity of regret is poorly identified: the parameter estimate is unstable and has a high standard error (which implies that the parameter is not significantly different from zero). Moreover, the estimated model with regret fits poorly the observed correlation between Second Mover effort and First Mover effort interacted with the prize, so regret does not replicate the behavior described by the reduced form results in Section 4.2.

Pressure. Choking under pressure (Baumeister, 1984), where an agent's performance deteriorates when incentives or stakes are higher, is also an implausible explanation of the discouragement effect. First, the Second Movers' marginal incentives do not depend on First Mover effort, so an incentives-based story for choking has no bite. Furthermore, if the level of the stakes matter Second Movers should choke more when their probability of winning is higher, i.e., when

[30] As noted above, the literature suggests that the probability weighting function's inflection point lies somewhat to the left of $P = 0.5$. Thus we also estimated the reduced form model with separate coefficients for the highest 20% of First Mover efforts (which give rise to particularly low Second Mover winning probabilities) and for the lowest 80%. The results were similar.

[31] In a theoretical analysis of regret with partial resolution of uncertainty, Krähmer and Stone (2008) make the same assumption. Formally, we estimate the same structural model as in Section 4.3.1, replacing the disappointment term with an expected regret term as follows

$$P_2(e_2, e_1)\rho \min\left\{v - C_2(e_2) - \max_{e_2^a \in \mathcal{A}\setminus e_2}\left(vP_2^W(e_2^a, e_2, e_1) - C_2(e_2^a)\right), 0\right\} +$$
$$(1 - P_2(e_2, e_1))\,\rho \min\left\{-C_2(e_2) - \max_{e_2^a \in \mathcal{A}\setminus e_2}\left(vP_2^L(e_2^a, e_2, e_1) - C_2(e_2^a)\right), 0\right\},$$

where ρ measures the intensity of regret and is assumed normally distributed, e_2^a represents an alternative Second Mover effort to the chosen effort e_2, $P_2^W(e_2^a, e_2, e_1) = \min\left\{\frac{e_2^a - e_1 + \gamma}{e_2 - e_1 + \gamma}, 1\right\}$ is the updated ex post probability of winning from having chosen e_2^a for a Second Mover who in fact wins with e_2 and $P_2^L(e_2^a, e_2, e_1) = \max\left\{\frac{e_2^a - e_2}{-e_2 + e_1 + \gamma}, 0\right\}$ is the ex post probability of winning function after losing (some updating occurs because winning or losing is somewhat informative about whether the random draws which determine the winner were favorable or unfavorable to the Second Mover).

the First Mover has worked *less hard*.

Collusion and reciprocity. Even though effort is socially wasteful, the subjects are not able to collude in our experiment: as explained in Section 2.2, the rotation-based matching algorithm that we use ensures that each pair of subjects plays a truly one-shot game: the pair meets only once and a subject's action in one round cannot have a direct or indirect effect on the actions of other subjects that the subject is paired with later on. A taste for reciprocity (Rabin, 1993) can sometimes allow agents to cooperate even in one-shot prisoners' dilemma-type games: in our set-up, low First Mover effort can be considered a kind action to be reciprocated with low effort, so positive reciprocity could conceivably allow the agents to coordinate on low effort. However, in Section 4.3.3 we find substantial variation in subjects' effort costs. This variation clouds inferences that subjects can make about a rival's intentions: subjects only meet the rival once and so will have difficulty distinguishing the rival's kind or unkind intention from a low or high cost of effort. Furthermore, our data show that Second Movers respond to a kinder action (lower First Mover effort) with a meaner action (higher effort) instead of the kinder action (lower effort) predicted by reciprocity, and if First Movers correctly anticipate that Second Movers will not reciprocate kindness it is not clear why they would wish to be kind themselves.

Equity. As we explain in Section 3.2, if the Second Movers disliked inequity in monetary payoffs their marginal incentives to exert effort would continue to be independent of First Mover effort, so such inequity aversion would not lead to a discouragement effect as Proposition 1 would continue to apply. Furthermore, we note that our model of expectations-based reference points can be re-interpreted as a model of equity in which agents like outputs, given here by monetary payoffs, to be in proportion to inputs, given here by efforts (see Gill and Stone, 2010, for details).

6 Conclusion

People compete all the time, e.g., for: promotions; bonuses; professional partnerships; elected positions; social status; and sporting trophies. In these situations the competitors exert effort to improve their prospects of success, and clear winners and losers emerge. Our results indicate that winners are elated while losers are disappointed, and that disappointment is the stronger emotion. In particular, we show that when our experimental subjects compete in a sequential-move real effort competition, they are loss averse around an endogenous expectations-based reference point which is conditioned on their own work effort and that of their rival. Disappointment aversion creates a discouragement effect, whereby a competitor slacks off when her rival works hard. Our results speak to the debate about the speed at which reference points adjust. Kőszegi and Rabin (2007) note that it is unclear how much time is needed between agents making their choices and the outcome occurring for the reference point to become choice-acclimating. Given the tiny temporal gap between the agents' effort choices and the outcome of the tournament, our results indicate that, at least in our competitive framework, the adjustment process is essentially instantaneous.

We hope that our theoretical model and empirical findings will provide a useful building block when predicting how people will behave in competitive situations. Furthermore, the findings may be helpful to principals when designing competitive environments. For example, employers will want to know how much they need to compensate employees for the expected disappointment implicit in different types of compensation schemes. They will also be interested in the degree to which a given compensation structure might impact on employees' work efforts, for example by creating asymmetries with some employees exerting a lot of effort and others becoming discouraged.

Appendix

A Proofs

A.1 Proof of Proposition 2

Using (1) and (7),

$$EU_2(e_2, e_1) = v\left(\frac{e_2 - e_1 + \gamma}{2\gamma}\right) - \lambda_2 v\left(\frac{\gamma^2 - (e_2 - e_1)^2}{4\gamma^2}\right) - C_2(e_2). \tag{17}$$

We use a proof by contradiction. Suppose that when e_1 increases from e_{11} to $e_{12} > e_{11}$, the Second Mover's optimal effort e_2^* increases from e_{21}^* to $e_{22}^* > e_{21}^*$. By the optimality of the Second Mover's effort choices

$$[EU_2(e_{21}^*, e_{11}) - EU_2(e_{22}^*, e_{11})] + [EU_2(e_{22}^*, e_{12}) - EU_2(e_{21}^*, e_{12})] \geq 0. \tag{18}$$

Using (17), we get the following:

$$EU_2(e_{21}^*, e_{11}) - EU_2(e_{21}^*, e_{12}) = v\left(\frac{-e_{11} + e_{12}}{2\gamma}\right) + \lambda_2 v\left(\frac{(e_{21}^* - e_{11})^2 - (e_{21}^* - e_{12})^2}{4\gamma^2}\right); \tag{19}$$

$$EU_2(e_{22}^*, e_{12}) - EU_2(e_{22}^*, e_{11}) = v\left(\frac{-e_{12} + e_{11}}{2\gamma}\right) + \lambda_2 v\left(\frac{(e_{22}^* - e_{12})^2 - (e_{22}^* - e_{11})^2}{4\gamma^2}\right). \tag{20}$$

Thus

$$(18) = \frac{\lambda_2 v}{2\gamma^2}(-e_{21}^* e_{11} + e_{21}^* e_{12} - e_{22}^* e_{12} + e_{22}^* e_{11}) = \frac{\lambda_2 v}{2\gamma^2}(e_{21}^* - e_{22}^*)(e_{12} - e_{11}) < 0 \tag{21}$$

given $\lambda_2 > 0$ for a disappointment averse Second Mover, which contradicts $(18) \geq 0$ from above.

Note that if there are multiple optima, the proof extends naturally to show that the highest optimal effort in response to e_{12} must lie weakly below the lowest in response to e_{11}. ■

A.2 Proof of Proposition 3

Using (9) and (17),

$$\frac{\partial EU_2(e_2, e_1)}{\partial e_2} = \frac{v}{2\gamma} + \frac{\lambda_2 v(e_2 - e_1)}{2\gamma^2} - b - ce_2; \tag{22}$$

$$\frac{\partial^2 EU_2(e_2, e_1)}{\partial e_2^2} = \frac{\lambda_2 v}{2\gamma^2} - c. \tag{23}$$

We assume that $2\gamma^2 c - \lambda_2 v > 0$, so the objective function is strictly concave.

Suppose first that the action space $\mathcal{A}$ is continuous. The first-order condition gives the following reaction function:

$$e_2^*(e_1) = \begin{cases} \bar{e} & \text{if } e_1 < \frac{\gamma v + \lambda_2 v\bar{e} - 2\gamma^2(b + c\bar{e})}{\lambda_2 v} \\ \frac{\gamma v - \lambda_2 v e_1 - 2\gamma^2 b}{2\gamma^2 c - \lambda_2 v} \in [0, \bar{e}] & \text{if } e_1 \in \left[\frac{\gamma v + \lambda_2 v\bar{e} - 2\gamma^2(b + c\bar{e})}{\lambda_2 v}, \frac{\gamma v - 2\gamma^2 b}{\lambda_2 v}\right] \\ 0 & \text{if } e_1 > \frac{\gamma v - 2\gamma^2 b}{\lambda_2 v} \end{cases} . \tag{24}$$

Given $\lambda_2 > 0$ and $2\gamma^2 c - \lambda_2 v > 0$, in the interior $\frac{de_2^*}{de_1}$ is clearly strictly negative and strictly decreasing in λ_2 and v.

Suppose second that the action space $\mathcal{A}$ is discrete. Take any $e_2 \in \mathcal{A}$ for which there exists a higher effort which is a best response to some $e_1 \in [0, \bar{e}]$ and a lower effort with the same property. Let e_2^+ be the next highest effort in $\mathcal{A}$ and let e_2^- be the next lowest effort in $\mathcal{A}$. Using (9) and (17), $EU_2(e_2^+, e_1) - EU_2(e_2, e_1)$

$$= \frac{v(e_2^+ - e_2)}{2\gamma} + \lambda_2 v\left(\frac{(e_2^+ - e_1)^2 - (e_2 - e_1)^2}{4\gamma^2}\right) - b(e_2^+ - e_2) - \frac{c((e_2^+)^2 - e_2^2)}{2} \tag{25}$$

$$= \frac{(2\gamma v - 4\gamma^2 b)(e_2^+ - e_2)}{4\gamma^2} + \left(\frac{\lambda_2 v - 2\gamma^2 c}{4\gamma^2}\right)((e_2^+)^2 - e_2^2) - \left(\frac{\lambda_2 v}{4\gamma^2}\right) 2e_1(e_2^+ - e_2). \tag{26}$$

The cut-off e_1 at which $EU_2(e_2^+, e_1) = EU_2(e_2, e_1)$ is given by

$$\breve{e}_1(e_2^+, e_2) = \frac{2\gamma v - 4\gamma^2 b}{2\lambda_2 v} - \left(\frac{2\gamma^2 c - \lambda_2 v}{\lambda_2 v}\right)\left(\frac{e_2^+ + e_2}{2}\right). \tag{27}$$

Given $\lambda_2 > 0$ and $2\gamma^2 c - \lambda_2 v > 0$ by assumption, the cut-offs are strictly decreasing in the Second Mover's effort. From Proposition 2, best responses are (weakly) falling in e_1. Thus if e_1 was continuous but e_2 was discrete, the cut-offs would represent the points at which the Second Mover's reaction function jumped down. As both are discrete, the cut-offs define the Second Mover's reaction function in the interior: e_2 is a best response for the Second Mover for and only for any $e_1 \in [\breve{e}_1(e_2^+, e_2), \breve{e}_1(e_2, e_2^-)] \cap \mathcal{A}$. The range $[\breve{e}_1(e_2^+, e_2), \breve{e}_1(e_2, e_2^-)]$ is of size

$$\breve{e}_1(e_2, e_2^-) - \breve{e}_1(e_2^+, e_2) = \left(\frac{2\gamma^2 c - \lambda_2 v}{\lambda_2 v}\right)\left(\frac{e_2^+ - e_2^-}{2}\right), \tag{28}$$

which is strictly decreasing in λ_2 and v.

That the cut-offs are strictly decreasing in e_2 is the discrete case analogue of the reaction function being strictly downward sloping in the continuous case. That the size of the ranges between the cut-offs is strictly decreasing in λ_2 and v is the discrete case analogue of the reaction function becoming strictly steeper in λ_2 and v in the continuous case. Note also the functional form similarity: supposing that the permitted e_2's increase in unit steps, $\frac{e_2^+ + e_2}{2} = e_2 + \frac{1}{2}$, so the rate of change of $\breve{e}_1(e_2^+, e_2)$ with respect to e_2 is the inverse of the slope of the reaction function in the continuous case. ■

B MSM: Further Details

B.1 Construction of Simulated Samples

The construction of each simulated sample is conditional on the First Mover efforts and prizes observed in the actual sample. Additionally we make random draws which will later be used to construct the unobservables appearing in the structural model. Specifically, for each simulated sample $s = 1, \ldots, S$ we construct matrices of dimensions $N \times 1$, $N \times 1$ and $N \times 10$, denoted $Q1_s$, $Q2_s$ and $Q3_s$ respectively. Each element of $Q1_s$, $Q2_s$ and $Q3_s$ contains a random draw from a standard uniform distribution. These matrices are held fixed throughout the estimation.[32] Given a trial parameter vector θ_t, the effort choice of the n^{th} Second Mover in the r^{th} round of the s^{th} sample is determined as follows:

1. The Second Mover is assigned values of the unobservables $\lambda_{2,n}$, μ_n and $\pi_{n,r}$ in accordance with the distributional assumptions made in Section 4.3.1. Draws from the normal distribution are found by transforming $Q1_s$ as follows:

$$\lambda_{2,n} = \widetilde{\lambda}_2 + \sigma_\lambda \Phi^{-1}(Q1_{s,n}), \tag{29}$$

   where Φ^{-1} denotes the inverse of the standard normal distribution function. Draws from the Weibull distribution are obtained by transforming $Q2_s$ and $Q3_s$ as follows:

$$\mu_n = \phi_\mu(-\ln(Q2_{s,n}))^{1/\varphi_\mu}; \tag{30}$$

$$\pi_{n,r} = \phi_\pi(-\ln(Q3_{s,n,r}))^{1/\varphi_\pi}. \tag{31}$$

   The values of the parameters $\widetilde{\lambda}_2$, σ_λ, φ_μ, φ_π, ϕ_μ and ϕ_π are obtained by extracting the relevant elements of θ_t.

2. Given the assigned values of $\lambda_{2,n}$, μ_n and $\pi_{n,r}$ and the remaining parameters of the cost of effort function, b, κ and δ_r for $r = 2, \ldots, 10$ as given by θ_t, the expected utility associated with each feasible Second Mover effort is computed using (7), (9) and (13).

3. The Second Mover is assigned the effort choice corresponding to the highest expected utility.

Steps 1-3 are repeated for each of the 10 rounds, the N Second Movers and the S simulated samples. Note that by comparing the expected utilities associated with each of the 49 feasible effort choices we fully account for the discreteness of effort. Additionally, the method of simulation does not rely on the objective function being well behaved.

[32] Thus as the trial parameter vector θ_t is adjusted the simulated samples vary only due to the change in θ_t and not due to variation in the underlying random draws. This is necessary to ensure convergence of the estimation routine (Stern, 1997).

B.2 Asymptotic Properties and Numerical Methods

Under the conditions in Pakes and Pollard (1989), $\widehat{\theta}$ is consistent and asymptotically normal. Specifically, with S fixed,

$$\sqrt{N}(\widehat{\theta}-\theta) \xrightarrow{d} N\left(0, \frac{S+1}{S}\left(D'WD\right)^{-1} D'W\Omega WD\left(D'WD\right)^{-1}\right) \quad \text{as} \quad N \to \infty, \tag{32}$$

where $\Omega = Ncov(M)$ is the covariance matrix of the sample moments normalized by the sample size, $W = plim(W_N)$ and

$$D = \frac{1}{S}\sum_{s=1}^{S} \frac{dM_s(\theta_t)}{d\theta_t'}\bigg|_{\theta_t=\theta}. \tag{33}$$

When implementing MSM, we use $S = 30$ simulated samples and therefore simulate 17700 pairings when using $N = 59$, and we estimate the weight matrix W_N using 2000 bootstrapped samples each containing N Second Movers sampled with replacement from the original sample.

The term $\frac{1}{S}\sum_{s=1}^{S} M_s(\theta_t)$ appearing in $J(\theta_t)$ in (14) is not a continuous function of the parameter vector θ_t as small changes in θ_t may cause discrete changes in some Second Movers' optimal effort choices. Consequently gradient and Hessian based optimization methods are unsuitable for minimizing $J(\theta_t)$. Instead we use Simulated Annealing in the form suggested by Goffe et al. (1994) to solve for the MSM estimates.

B.3 Moments and Goodness of Fit

Moment	Description	Primarily Identifying
$\mathrm{SD}(e_{2,n,r})$	Standard deviation of Second Mover effort	$\phi_\pi,\phi_\mu,\varphi_\pi,\varphi_\mu,\sigma_\lambda$
$\mathrm{Prop}(e_{2,n,r}<15)$; $\mathrm{Prop}(e_{2,n,r}>35)$	Proportions of Second Mover efforts below 15 and above 35	$\phi_\pi,\phi_\mu,\varphi_\pi,\varphi_\mu,\sigma_\lambda$
$\mathrm{SD}(e_{2,n,r}-e_{2,n,r-1})$	Standard deviation of the round on round change in Second Mover effort	ϕ_π,φ_π
$\mathrm{Corr}(e_{2,n,r},e_{2,n,r-1})$; $\mathrm{Corr}(e_{2,n,r},e_{2,n,r-2})$	1st and 2nd order autocorrelations in Second Mover effort	$\phi_\mu,\varphi_\mu,\sigma_\lambda$
$\mathrm{Mean}(e_{2,n,r})$ for $r=1,\dots,10$	Round specific means of Second Mover effort	b, δ_r for $r=2,\dots,10$
$\mathrm{Corr}(e_{2,n,r},v_{n,r} \mid e_{1,n,r},e_{1,n,r}v_{n,r},RD,FE)$	Correlation between Second Mover effort and the prize after partialing out linear additive effects of First Mover effort, First Mover effort interacted with the prize, round dummies and Second Mover specific fixed effects	κ
$\mathrm{Corr}(e_{2,n,r},e_{1,n,r} \mid v_{n,r},e_{1,n,r}v_{n,r},RD,FE)$	Correlation between Second Mover effort and First Mover effort after partialing out linear additive effects of the prize, First Mover effort interacted with the prize, round dummies and Second Mover specific fixed effects	$\widetilde{\lambda}_2$
$\mathrm{Corr}(e_{2,n,r},v_{n,r}e_{1,n,r} \mid e_{1,n,r},v_{n,r},RD,FE)$	Correlation between Second Mover effort and First Mover effort interacted with the prize after partialing out linear additive effects of First Mover effort, the prize, round dummies and Second Mover specific fixed effects	$\widetilde{\lambda}_2$
$\mathrm{Pc}_j\mathrm{Corr}_n(e_{2,n,r},v_{n,r}\|e_{1,n,r},e_{1,n,r}v_{n,r},RT)$ for $j=17,33,50,66,83$	j^{th} percentile of the Second Mover specific correlation between Second Mover effort and the prize after partialing out linear additive effects of First Mover effort, First Mover effort interacted with the prize and a linear round trend	$\phi_\pi,\phi_\mu,\varphi_\pi,\varphi_\mu$
$\mathrm{Pc}_j\mathrm{Corr}_n(e_{2,n,r},e_{1,n,r}\|v_{n,r},e_{1,n,r}v_{n,r},RT)$ for $j=17,33,50,66,83$	j^{th} percentile of the Second Mover specific correlation between Second Mover effort and First Mover effort after partialing out linear additive effects of the prize, First Mover effort interacted with the prize and a linear round trend	σ_λ
$\mathrm{Pc}_j\mathrm{Corr}_n(e_{2,n,r},v_{n,r}e_{1,n,r}\|e_{1,n,r},v_{n,r},RT)$ for $j=17,33,50,66,83$	j^{th} percentile of the Second Mover specific correlation between Second Mover effort and First Mover effort interacted with the prize after partialing out linear additive effects of First Mover effort, the prize and a linear round trend	σ_λ
$\mathrm{Mean}(e_{2,n,r}\|e_{1,n,r}<23\cap v_{n,r}<1.33)$	Mean of Second Mover effort conditional on low First Mover effort and low prize	κ, $\widetilde{\lambda}_2$
$\mathrm{Mean}(e_{2,n,r}\|e_{1,n,r}<23\cap v_{n,r}>2.55)$	Mean of Second Mover effort conditional on low First Mover effort and high prize	κ, $\widetilde{\lambda}_2$
$\mathrm{Mean}(e_{2,n,r}\|e_{1,n,r}>28\cap v_{n,r}<1.33)$	Mean of Second Mover effort conditional on high First Mover effort and low prize	κ, $\widetilde{\lambda}_2$
$\mathrm{Mean}(e_{2,n,r}\|e_{1,n,r}>28\cap v_{n,r}>2.55)$	Mean of Second Mover effort conditional on high First Mover effort and high prize	κ, $\widetilde{\lambda}_2$

Notes: RD, FE and RT denote round dummies, Second Mover specific fixed effects and a linear round trend.
Partialing out is accomplished by working with the residuals from regressions of the dependent variables on the control variables.

Table 4: Description of Moments.

	Observed Moment	Bootstrapped SD	Fitted Moment	z Test for Difference
$\text{SD}(e_{2,n,r})$	5.875	0.497	5.496	-0.760
$\text{Corr}(e_{2,n,r}, e_{2,n,r-1})$	0.652	0.062	0.633	-0.307
$\text{Corr}(e_{2,n,r}, e_{2,n,r-2})$	0.596	0.085	0.603	0.087
$\text{SD}(e_{2,n,r} - e_{2,n,r-1})$	4.828	0.719	4.645	-0.255
$\text{Mean}(e_{2,n,1})$	21.763	0.784	21.602	-0.205
$\text{Mean}(e_{2,n,2})$	23.458	0.633	23.264	-0.305
$\text{Mean}(e_{2,n,3})$	24.831	0.650	24.933	0.158
$\text{Mean}(e_{2,n,4})$	25.203	0.585	25.360	0.268
$\text{Mean}(e_{2,n,5})$	25.119	0.737	24.927	-0.260
$\text{Mean}(e_{2,n,6})$	24.898	0.897	25.233	0.373
$\text{Mean}(e_{2,n,7})$	25.763	0.798	25.968	0.258
$\text{Mean}(e_{2,n,8})$	26.169	0.673	26.310	0.208
$\text{Mean}(e_{2,n,9})$	26.254	0.860	26.401	0.171
$\text{Mean}(e_{2,n,10})$	26.729	0.774	26.592	-0.177
$\text{Corr}(e_{2,n,r}, v_{n,r} \mid e_{1,n,r}, e_{1,n,r}v_{n,r}, RD, FE)$	0.124	0.044	0.084	-0.905
$\text{Corr}(e_{2,n,r}, e_{1,n,r} \mid v_{n,r}, e_{1,n,r}v_{n,r}, RD, FE)$	0.041	0.042	0.003	-0.916
$\text{Corr}(e_{2,n,r}, v_{n,r}e_{1,n,r} \mid e_{1,n,r}, v_{n,r}, RD, FE)$	-0.095	0.047	-0.038	1.200
$\text{Pc}_{17}\text{Corr}_n(e_{2,n,r}, v_{n,r} \mid e_{1,n,r}, e_{1,n,r}v_{n,r}, RT)$	-0.275	0.098	-0.179	0.975
$\text{Pc}_{33}\text{Corr}_n(e_{2,n,r}, v_{n,r} \mid e_{1,n,r}, e_{1,n,r}v_{n,r}, RT)$	0.033	0.079	0.043	0.124
$\text{Pc}_{50}\text{Corr}_n(e_{2,n,r}, v_{n,r} \mid e_{1,n,r}, e_{1,n,r}v_{n,r}, RT)$	0.222	0.071	0.212	-0.145
$\text{Pc}_{66}\text{Corr}_n(e_{2,n,r}, v_{n,r} \mid e_{1,n,r}, e_{1,n,r}v_{n,r}, RT)$	0.388	0.041	0.360	-0.675
$\text{Pc}_{83}\text{Corr}_n(e_{2,n,r}, v_{n,r} \mid e_{1,n,r}, e_{1,n,r}v_{n,r}, RT)$	0.469	0.051	0.523	1.051
$\text{Pc}_{17}\text{Corr}_n(e_{2,n,r}, e_{1,n,r} \mid v_{n,r}, e_{1,n,r}v_{n,r}, RT)$	-0.328	0.052	-0.386	-1.118
$\text{Pc}_{33}\text{Corr}_n(e_{2,n,r}, e_{1,n,r} \mid v_{n,r}, e_{1,n,r}v_{n,r}, RT)$	-0.218	0.061	-0.204	0.224
$\text{Pc}_{50}\text{Corr}_n(e_{2,n,r}, e_{1,n,r} \mid v_{n,r}, e_{1,n,r}v_{n,r}, RT)$	0.019	0.089	-0.027	-0.514
$\text{Pc}_{66}\text{Corr}_n(e_{2,n,r}, e_{1,n,r} \mid v_{n,r}, e_{1,n,r}v_{n,r}, RT)$	0.179	0.064	0.141	-0.585
$\text{Pc}_{83}\text{Corr}_n(e_{2,n,r}, e_{1,n,r} \mid v_{n,r}, e_{1,n,r}v_{n,r}, RT)$	0.361	0.064	0.350	-0.169
$\text{Pc}_{17}\text{Corr}_n(e_{2,n,r}, v_{n,r}e_{1,n,r} \mid e_{1,n,r}, v_{n,r}, RT)$	-0.194	0.080	-0.208	-0.175
$\text{Pc}_{33}\text{Corr}_n(e_{2,n,r}, v_{n,r}e_{1,n,r} \mid e_{1,n,r}, v_{n,r}, RT)$	0.019	0.067	0.001	-0.268
$\text{Pc}_{50}\text{Corr}_n(e_{2,n,r}, v_{n,r}e_{1,n,r} \mid e_{1,n,r}, v_{n,r}, RT)$	0.146	0.057	0.169	0.395
$\text{Pc}_{66}\text{Corr}_n(e_{2,n,r}, v_{n,r}e_{1,n,r} \mid e_{1,n,r}, v_{n,r}, RT)$	0.298	0.068	0.305	0.101
$\text{Pc}_{83}\text{Corr}_n(e_{2,n,r}, v_{n,r}e_{1,n,r} \mid e_{1,n,r}, v_{n,r}, RT)$	0.474	0.050	0.483	0.170
$\text{Mean}(e_{2,n,r} \mid e_{1,n,r}<23 \cap v_{n,r}<1.33)$	23.821	0.867	24.121	0.346
$\text{Mean}(e_{2,n,r} \mid e_{1,n,r}<23 \cap v_{n,r}>2.55)$	25.485	0.814	25.595	0.135
$\text{Mean}(e_{2,n,r} \mid e_{1,n,r}>28 \cap v_{n,r}<1.33)$	25.836	0.975	25.265	-0.586
$\text{Mean}(e_{2,n,r} \mid e_{1,n,r}>28 \cap v_{n,r}>2.55)$	25.050	1.208	25.665	0.509
$\text{Prop}(e_{2,n,r} < 15)$	0.029	0.010	0.033	0.401
$\text{Prop}(e_{2,n,r} > 35)$	0.015	0.008	0.017	0.206

Notes: See Table 4 for a description of the moments. Observed moments are computed from the sample and fitted moments are computed using parameter estimates from the preferred specification.

Table 5: Goodness of fit of the preferred specification.

C Experimental Instructions [Intended for online publication]

Please open the brown envelope you have just collected. I am reading from the four page instructions sheet which you will find in your brown envelope. [**Open brown envelope**]

Thank you for participating in this session. There will be a number of pauses for you to ask questions. During such a pause, please raise your hand if you want to ask a question. Apart from asking questions in this way, you must not communicate with anybody in this room. Please now turn off mobile phones and any other electronic devices. These must remain turned off for the duration of this session. Are there any questions?

You have been allocated to a computer booth according to the number on the card you selected as you came in. You must not look into any of the other computer booths at any time during this session. As you came in you also selected a white sealed envelope. Please now open your white envelope. [**Open white envelope**]

Each white envelope contains a different four digit Participant ID number. To ensure anonymity, your actions in this session are linked to this Participant ID number and at the end of this session you will be paid by Participant ID number. You will be paid a show up fee of £4 together with any money you accumulate during this session. The amount of money you accumulate will depend partly on your actions, partly on the actions of others and partly on chance. All payments will be made in cash in another room. Neither I nor any of the other participants will see how much you have been paid. Please follow the instructions that will appear shortly on your computer screen to enter your four digit Participant ID number. [**Enter four digit Participant ID number**] Please now return your Participant ID number to its envelope, and keep this safe as your Participant ID number will be required for payment at the end.

This session consists of 2 practice rounds, for which you will not be paid, followed by 10 paying rounds with money prizes. In each round you will undertake an identical task lasting 120 seconds. The task will consist of a screen with 48 sliders. Each slider is initially positioned at 0 and can be moved as far as 100. Each slider has a number to its right showing its current position. You can use the mouse in any way you like to move each slider. You can readjust the position of each slider as many times as you wish. Your "points score" in the task will be the number of sliders positioned at exactly 50 at the end of the 120 seconds. Are there any questions?

Before the first practice round, you will discover whether you are a "First Mover" or a "Second Mover". You will remain either a First Mover or a Second Mover for the entirety of this session.

In each round, you will be paired. One pair member will be a First Mover and the other will be a Second Mover. The First Mover will undertake the task first, and then the Second Mover will undertake the task. The Second Mover will see the First Mover's points score before starting the task.

In each paying round, there will be a prize which one pair member will win. Each pair's prize will be chosen randomly at the beginning of the round and will be between £0.10 and £3.90. The winner of the prize will depend on the difference between the First Mover's and the Second Mover's points scores and some element of chance. If the points scores are the same, each pair member will have a 50% chance of winning the prize. If the points scores are not the same, the chance of winning for the pair member with the higher points score increases by 1 percentage point for every increase of 1 in the difference between the points scores, while the chance of winning for the pair member with the lower points score correspondingly decreases by 1 percentage point. The table at the end of these instructions gives the chance of winning for any points score difference. Please look at this table now. [**Look at table**] Are there any questions?

During each task, a number of pieces of information will appear at the top of your screen, including the time remaining, the round number, whether you are a First Mover or a Second Mover, the prize for the round and your points score in the task so far. If you are a Second Mover, you will also see the points score of the First Mover you are paired with.

After both pair members have completed the task, each pair member will see a summary screen showing their own points score, the other pair member's points score, their probability of winning, the prize for the round and whether they were the winner or the loser of the round.

We will now start the first of the two practice rounds. In the practice rounds, you will be paired with an automaton who behaves randomly. Before we start, are there any questions? Please look at your screen now. [**First practice round**] Before we start the second practice round, are there any questions? Please look at your screen now. [**Second practice round**] Are there any questions?

The practice rounds are finished. We will now move on to the 10 paying rounds. In every paying round, each First Mover will be paired with a Second Mover. The pairings will be changed after every round and pairings will not depend on your previous actions. You will not be paired with the same person twice. Furthermore, the pairings are done in such a way that the actions you take in one round cannot affect the actions of the people you will be paired with in later rounds. This also means that the actions of the person you are paired with in a given round cannot be affected by your actions in earlier rounds. (If you are interested, this is because you will not be paired with a person who was paired with someone who had been paired with you, and you will not be paired with a person who was paired with someone who had been paired with someone who had been paired with you, and so on.) Are there any questions?

We will now start the 10 paying rounds. There will be no pauses between the rounds. Before we start the paying rounds, are there any remaining questions? There will be no further opportunities to ask questions. Please look at your screen now. [**10 paying rounds**]

The session is now complete. Your total cash payment, including the show up fee, is displayed on your screen. Please leave the room one by one when asked to do so to receive your payment. Remember to bring the envelope containing your four digit Participant ID number with you but please leave all other materials on your desk. Thank you for participating.

Difference in points scores	Chance of winning prize for Mover with higher score	Chance of winning prize for Mover with lower score
0	50%	50%
1	51%	49%
2	52%	48%
3	53%	47%
4	54%	46%
5	55%	45%
6	56%	44%
7	57%	43%
8	58%	42%
9	59%	41%
10	60%	40%
11	61%	39%
12	62%	38%
13	63%	37%
14	64%	36%
15	65%	35%
16	66%	34%
17	67%	33%
18	68%	32%
19	69%	31%
20	70%	30%
21	71%	29%
22	72%	28%
23	73%	27%
24	74%	26%
25	75%	25%
26	76%	24%
27	77%	23%
28	78%	22%
29	79%	21%
30	80%	20%
31	81%	19%
32	82%	18%
33	83%	17%
34	84%	16%
35	85%	15%
36	86%	14%
37	87%	13%
38	88%	12%
39	89%	11%
40	90%	10%
41	91%	9%
42	92%	8%
43	93%	7%
44	94%	6%
45	95%	5%
46	96%	4%
47	97%	3%
48	98%	2%
49	Not possible as there are only 48 sliders	
50	Not possible as there are only 48 sliders	

Table 6: Chance of winning in a given round.

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