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ABSTRACT

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

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. Our theory predicts that a disappointment averse agent, who is loss averse around her endogenous 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.

JEL Classification: C91, D03

Keywords: disappointment aversion, loss aversion, reference-dependent preferences, reference point adjustment, expectations, tournament, real effort experiment, slider task

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The sudden disappointment of a hope leaves a scar which the ultimate fulfillment of that hope never entirely removes.[1]

England fullback Delon Armitage is determined to put his misery at being overlooked by the British & Irish Lions behind him when he runs out to face Argentina at Old Trafford on Saturday ... The occasion will not be lost on Armitage, although he is struggling to get past the disappointment of missing out on a Lions call after an excellent first Test season ... 'I was really, really disappointed about it,' he said. 'I still need to get over it a little bit.' [2]

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. 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.[3] 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. If agents care only about money and the cost of effort then the Second Mover's work effort should not depend on the effort of the First Mover. However, as predicted by our theory of disappointment, 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.

Our contribution is three-fold: methodological; theoretical; and empirical. From a methodological perspective, we develop a novel real effort task designed to facilitate robust statistical inference. Early experiments implementing costly activities used a monetary cost function which mimics effort by specifying output as a function of how much money subjects contribute (e.g., Bull et al., 1987, in a tournament context). Increasingly, laboratory experiments have featured real effort tasks.[4] Real effort generates greater external validity, but makes precise quantification difficult (Falk and Fehr, 2003). The main advantage of our slider task is that it allows a fine and accurate measure of effort over a short time scale. Thus we interpret performance in the task as effort exerted and we can use repeated observations of the same subjects to control for

[1] Thomas Hardy, as quoted by Gibson (1996, p. 74).

[2] ESPN Scrum, 4 June 2009, www.scrum.com/england/rugby/story/97635.html

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

[4] See Section 2.1.2 for examples of different real effort tasks. Recently experiments involving real effort tournaments have become popular (e.g., van Dijk et al., 2001; Gneezy et al., 2003; Niederle and Vesterlund, 2007; Carpenter et al., 2007; Charness and Villeval, 2009).

learning-by-doing and persistent unobserved heterogeneity. We believe that our task will prove valuable to researchers in designing future experiments with real effort.

From a theoretical perspective, we extend disappointment aversion to situations in which agents compete. Existing models of disappointment aversion (e.g., Bell, 1985; Loomes and Sugden, 1986; Gul, 1991; Shalev, 2000; Delquié and Cillo, 2006a, 2006b; Kőszegi and Rabin, 2006, 2007) build on the idea that agents are sensitive to deviations from what they expected to receive. We model disappointment aversion as loss aversion around an agent's expected payoff, so losses relative to this expectation are more painful than equal-sized gains are pleasurable.[5] In our competitive framework, this expected payoff is determined endogenously by the agents' effort choices. Thus we model agents as holding reference-dependent preferences with an endogenous reference point given by choice-acclimating (Kőszegi and Rabin, 2007) expectations, and we assume that agents anticipate the impact of effort on their reference point.

Our theory predicts an empirically testable *discouragement effect* whereby the Second Mover responds negatively to the First Mover's effort. Thus First and Second Movers' efforts are strategic substitutes. This discouragement effect becomes more powerful in the strength of disappointment aversion, measured by the size of the kink in utility induced by loss aversion, and in the value of the prize. A disappointment averse Second Mover becomes discouraged even though we impose probabilities of winning the prize which are linear in the difference in the agents' efforts, so that, in the canonical tournament model with a separable cost of effort, the First Mover's effort has no effect on the Second Mover's marginal incentives. Note that the endogeneity of the reference point is crucial. Most of the literature on loss aversion assumes a fixed reference point, but with such a reference point, even if given by a prior expectation, the standard model predicts no discouragement effect.

From an empirical perspective, we offer evidence of disappointment aversion from a linear random effects panel regression and from structural estimation using the Method of Simulated Moments. We find significant evidence of disappointment aversion. The reduced form analysis shows that subjects' behavior in our experiment is inconsistent with the standard model, but instead exhibits the discouragement effect predicted by our theory of disappointment. Additionally, we use structural modeling to estimate the strength of disappointment aversion on average and the heterogeneity in disappointment aversion across the population. Both estimation methods exploit identifying variation obtained from the properties of the slider task together with our experimental design. Specifically, the value of the prize is drawn randomly each time a First and Second Mover are paired, while the fineness of our measure of effort allows us to observe precisely how Second Movers respond to the prize and the effort choice of the First Mover they are paired with.

Our empirical results 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

[5]Loss aversion is a fundamental component of Kahneman and Tversky (1979)'s Prospect Theory. Kahneman and Tversky (2000) collect a number of papers providing empirical support for loss aversion in numerous different contexts, while DellaVigna (2009) surveys some more recent evidence.

others.

Our work is complementary to that of Abeler et al. (2009) and Crawford and Meng (2009) who also find evidence for expectations-based reference-dependent preferences in the context of effort provision. Abeler et al. run a laboratory experiment with a non-competitive design 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. Abeler et al. do not estimate any structural parameters, while we are able to estimate the strength of disappointment aversion. Crawford and Meng use field data on taxi driver labor supply to estimate the strength of loss aversion around rational expectations-based daily income and hours targets.[6] In contrast to our model, the reference point is taken to be fixed when the agent chooses how hard to work. Our paper is also related to the existing empirical literature on disappointment aversion in the absence of effort provision. A number of papers test for disappointment aversion using choices over, or bids for, lotteries. Loomes and Sugden (1987) provide an early example, while recent instances include Choi et al. (2007) and Sonsino (2008).

Finally, 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).

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 theory of disappointment aversion when agents compete. Section 4 presents the empirical analysis. Section 5 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 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.[7] 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). At the end of the experiment, subjects were asked to report their gender (but could withhold this information). Subjects were paid privately in cash by the laboratory administrator. The experiment was programmed in z-Tree (Fischbacher, 2007).

[6] Camerer et al. (1997) and Doran (2009) also find evidence of taxi driver loss aversion.

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

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 and explain its advantages in relation to the existing stock of real effort tasks.

2.1.1 Description of the Slider Task

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 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. As explained in Section 2.1.2, we interpret a subject's point score as effort exerted in the task. 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.

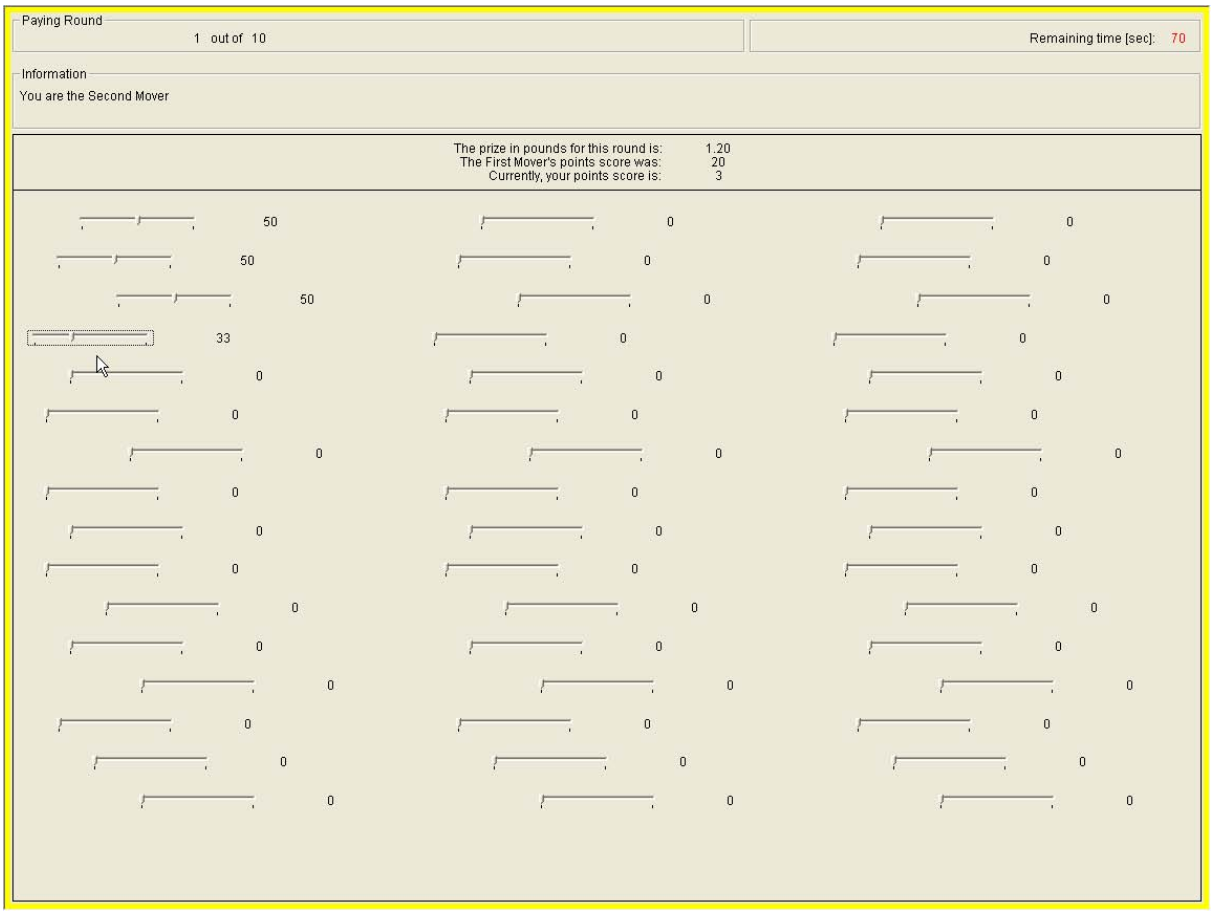
Figure 1: Schematic representation of a slider.

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.[8] 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.

2.1.2 Advantages of the Slider Task

The slider task has a number of desirable attributes. First, the slider task is simple to communicate and to understand, and does not require or test pre-existing knowledge. Second, unlike solving mathematical problems (Sutter and Weck-Hannemann, 2003), counting, decoding or

[8]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.

entering strings of characters (Chow, 1983), solving word games (Burrows and Loomes, 1994), answering general knowledge questions (Hoffman et al., 1994), negotiating mazes (Gneezy et al., 2003) or performing numerical optimization (van Dijk et al., 2001), the slider task is identical across repetitions. Third, the task allows a fine measure of performance and involves little randomness, so the number of correctly positioned sliders corresponds closely to the effort exerted by the subject. Thus we interpret a subject's point score as effort exerted in the task. Fourth, there is no scope for guessing, which complicates the design and interpretation of some existing tasks such as those based on counting characters or numerical optimization.

These attributes are also shared by the envelope filling task (Konow, 2000), in which subjects stuff real envelopes with letters. Crucially, however, the slider task allows a fine measure of effort within a short time scale. Furthermore, because the task is computerized, it is easy to implement and allows flexible real-time subject interactions. In Section 4 we see that with 48 sliders and an allotted time of 120 seconds, measured effort varies from 0 to over 40. Thus substantial variation in behavior can be observed, and by getting subjects to repeat the identical task many times the experimenter can control for persistent unobserved heterogeneity using panel data methods. This allows robust statistical inference. For example, we use repeated observations of the same subjects to estimate the distribution of effort costs, enabling structural estimation of the strength of disappointment aversion on average and the heterogeneity in disappointment aversion across the population. Thus the task's design overcomes the principal drawback of

using real effort up to now, namely that "Since the experimenter does not know the workers' effort cost, it is not possible to derive precise quantitative predictions" (Falk and Fehr, 2003, p. 404).

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 2.1.1, 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. 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 (as used recently by, e.g., Dal Bó, 2005). 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 2.1.2, we interpret a subject's points score in the slider task as effort exerted. 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,

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

with $\gamma \geq \overline{e}$ to ensure that $P_i \in [0, 1]$.[9] Throughout we focus on the behavior of the Second Mover conditional on the First Mover's effort e_1.

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 $C_2(e_2)$,[10] so

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

The underlying assumption is that because the (non-monetary) effort cost is sunk before the winner of the tournament is determined, the effort choice does not affect risk preferences over the monetary payoff from the tournament. 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.

[9] Che and Gale (2000) call this a piece-wise linear difference-form success function.

[10] In their related work, Abeler et al. (2009) and Crawford and Meng (2009) make equivalent separability assumptions.

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 absence of 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 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 is loss averse around a *fixed* reference point (Section 3.3 elaborates) or exhibits any degree of risk aversion over her monetary payoff. 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; Gul, 1991; Shalev, 2000; Delquié and Cillo, 2006a, 2006b; 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 most of the literature in embedding disappointment aversion in a loss aversion-type framework.[11] 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

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

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 $x = 0$.

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. Models and tests of loss aversion generally incorporate narrow framing, either implicitly or explicitly (DellaVigna, 2009). Barberis et al. (2006) provide evidence that attitudes towards small gambles can only be explained by first-order loss aversion together

[11] Instead, Gul (1991) uses probability weighting, while Loomes and Sugden (1986) insist on the differentiability of utility. 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.

with the narrow framing of individual gambles, while Read et al. (1999) survey the broader evidence on narrow framing.

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, an exogenous 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 an exogenous reference point, we assume that a disappointment averse Second Mover is loss averse around an *endogenous* reference point equal to her expected material utility given the effort levels that are actually chosen,[12] 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*.[13]

To operationalize our model, we linearize material utility and gain-loss utility.[14] 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.[15] Thus we define disappointment aversion as follows.

[12] In a single agent set-up, Bell (1985) and Loomes and Sugden (1986) also use a reference point equal to expected material utility given the chosen action. Delquié and Cillo (2006a, 2006b) and Kőszegi and Rabin (2006, 2007) argue that in a stochastic environment, the reference point itself should be taken to be a lottery, with an agent comparing the outcome to all the possible outcomes in the reference lottery and weighting each comparison by the probability of the relevant reference outcome. It is straightforward to show that in the linear environment considered below the reference lottery approach collapses to our single reference point set-up.

[13] Technically our game is psychological (Geanakoplos et al., 1989) 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. In Kőszegi and Rabin (2006), by contrast, utilities depend only on initial beliefs as the reference point is given by a prior expectation which does not update in response to the chosen action (although an equilibrium consistency requirement is imposed on the expectation).

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

[15] 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.

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.*

We can then express a disappointment averse Second Mover's expected utility as[16]

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

and we let

$$\Lambda_2(e_2 - e_1) \equiv -\lambda_2 vP_2(1 - P_2) \tag{8}$$

represent the extra term introduced into expected utility by disappointment aversion. (Recall from Section 3.2 that loss aversion around a fixed reference point, including one given by a prior expectation, or risk aversion in the absence of an endogenous reference point do not introduce a similar term.)

We call Λ_2 the Second Mover's *disappointment deficit* as it is always negative for $\lambda_2 > 0$ (strictly negative for $P_i \notin \{0, 1\}$): 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 of the Second Mover's two-point distribution of monetary payoffs is given by $vP_2(1 - P_2)$, which is strictly concave in P_2 and maximized at $P_2 = \frac{1}{2}$, so given the linearity of P_2 in $e_2 - e_1$ the disappointment deficit is strictly convex in the difference in efforts and at its most negative where the efforts are equal.

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.

The convexity of the disappointment deficit is critical to understanding how the Second Mover responds to the First Mover's effort choice. 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. This puts the Second Mover at a point on her disappointment deficit curve with a lower slope (less positive or more negative) so the Second Mover's effort has a smaller (again less positive or more negative) effect on the disappointment deficit, and hence the Second Mover has a lower

[16] In the context of desert preferences, whereby an agent's expectation represents how much she feels she deserves given how hard she was worked in comparison to her rival, Gill and Stone (2009) derive an equivalent formulation which they use to analyze simultaneous effort choices in a purely theoretical framework. Gill and Stone permit $g_2 < 0$ to model agents who feel guilty about doing better than deserved. All of our theoretical and empirical analysis continues to hold if we allow $g_2 < 0$ here.

marginal incentive to exert effort. 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.[17]

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 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. The variance of the monetary payoff goes up in the size of the prize, and the stronger is disappointment aversion, the greater the weight put on this variance.

[17] 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.

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, our estimation strategies exploit identifying variation obtained from the properties of our slider task together with the experimental design. In Section 4.4 we discuss how our results provide evidence for endogenous choice-acclimating reference points and we relate our estimate of the disappointment aversion parameter to existing estimates of loss aversion.

We analyze the behavior of Second Movers conditional on the effort choices of the First Movers. 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 requires 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.

As noted in Section 2.1.1, we interpret the number of sliders correctly positioned within the allotted time, i.e., the points score, as the effort exerted by the subject. We comment here on two features of this effort measure. First, as explained in Section 2.1.2, the design of our slider task ensures that points scores correspond closely to effort exerted. Second, while the slider task provides a fine 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 explained below, discrete effort choices are easily accommodated in our structural model.

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 and this subject is dropped from our preferred sample.[18] However, we show 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 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.

[18]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.

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.

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.[19] 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:

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

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

[19] 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.

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_ω^2, while $\epsilon_{n,r}$ is assumed to be identically and independently distributed over rounds and Second Movers with a variance σ_ϵ^2.

	Preferred Sample 59 Second Movers		Full Sample 60 Second Movers	
	Coefficient	z value (p value)	Coefficient	z value (p value)
First Mover effort	0.044	0.898 (0.369)	0.047	0.963 (0.336)
Prize	1.639***	2.724 (0.006)	1.655***	2.794 (0.005)
Prize×First Mover effort	−0.049**	−2.083 (0.037)	−0.050**	−2.179 (0.029)
d_2	1.689**	2.381 (0.017)	1.655**	2.368 (0.018)
d_3	3.084***	4.325 (0.000)	3.034***	4.323 (0.000)
d_4	3.448***	4.838 (0.000)	3.369***	4.801 (0.000)
d_5	3.322***	4.650 (0.000)	3.279***	4.661 (0.000)
d_6	3.262***	4.577 (0.000)	3.193***	4.554 (0.000)
d_7	4.123***	5.756 (0.000)	4.043***	5.734 (0.000)
d_8	4.567***	6.341 (0.000)	4.487***	6.330 (0.000)
d_9	4.709***	6.582 (0.000)	4.632***	6.579 (0.000)
d_{10}	5.180***	7.148 (0.000)	5.066***	7.115 (0.000)
Intercept	19.777***	14.126 (0.000)	19.392***	13.400 (0.000)
σ_ω	4.288		5.342	
σ_ϵ	3.852		3.826	
$N \times R$	590		600	
χ^2 test for no significant difference between men and women	4.16 $df = 3, p = 0.242$		2.94 $df = 3, p = 0.235$	
Hausman test for random versus fixed effects	2.43 $df = 12, p = 0.998$		2.43 $df = 12, p = 0.998$	

Notes: *, ** and *** denote significance at the 10%, 5% and 1% levels. *df* denotes degrees of freedom.

Table 2: Random effects regressions for Second Mover effort.

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 10 slider increase in First Mover effort decreases Second Mover effort by approximately 1.5 sliders. Furthermore, there are large and significant positive prize effects, and we find that the persistent unobserved individual characteristics explain more of the variation in behavior than the transitory unobservables. The round dummies reveal significant increases in effort over the 10 rounds which we interpret as a reduction in the marginal cost of effort due to learning-by-doing.

Additional regressions, not reported, allow the coefficients on First Mover effort, the prize and the interaction of these two variables to differ between men and women. No significant gender differences were found. This suggests that Niederle and Vesterlund (2007)'s finding that men have a stronger preference for competition compared to women cannot be explained by differential levels of disappointment aversion across gender when agents compete.

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 the empirical specification, the estimation strategy, including a discussion of identification, and the results.

4.3.1 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. A cost of effort that is declining over rounds due to learning is therefore 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.[20]

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

[20] In Section 4.3.3 we show that replacing the Weibull distribution with the normal distribution reduces the model's goodness of fit.

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 bootstrap sampling of Second Movers with replacement to estimate W_N. Efficiency is maximized by setting W_N to be the inverse of N times the covariance matrix of the sample moments, which yields an Optimally Weighted Minimum Distance estimator (OWMD). However, it is well known that this choice of W_N can introduce finite sample bias (see for example Altonji and Segal, 1996). Thus our preferred estimator uses a weight matrix with diagonal elements equal to the inverse of N times the variances of the sample moments and zeros elsewhere, which yields a Diagonally Weighted Minimum Distance estimator (DWMD). 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

	Preferred Spec.	Robustness Checks		
	DWMD	OWMD	DWMD	DWMD
	59 Second Movers	59 Second Movers	59 Second Movers	60 Second Movers
	Weibull Costs	Weibull Costs	Normal Costs	Weibull Costs
$\widetilde{\lambda}_2$	1.724	1.497	1.199	1.409
	(0.479)[0.000]	(0.258)[0.000]	(0.347)[0.001]	(0.323)[0.000]
σ_λ	1.433	1.153	1.298	1.508
	(0.492)[0.004]	(0.154)[0.000]	(0.308)[0.000]	(0.455)[0.001]
b	−0.532	−0.566	−0.522	−0.506
	(0.033)[0.000]	(0.013)[0.000]	(0.017)[0.000]	(0.017)[0.000]
κ	1.868	2.069	2.568	1.808
	(0.095)[0.000]	(0.037)[0.000]	(0.053)[0.000]	(0.074)[0.000]
δ_2	−0.162	−0.198	−0.163	−0.171
	(0.043)[0.000]	(0.033)[0.000]	(0.034)[0.000]	(0.056)[0.000]
δ_3	−0.265	−0.313	−0.321	−0.301
	(0.040)[0.000]	(0.030)[0.000]	(0.050)[0.000]	(0.059)[0.000]
δ_4	−0.314	−0.332	−0.344	−0.306
	(0.051)[0.000]	(0.032)[0.000]	(0.031)[0.000]	(0.074)[0.000]
δ_5	−0.315	−0.394	−0.341	−0.285
	(0.040)[0.000]	(0.032)[0.000]	(0.063)[0.000]	(0.072)[0.000]
δ_6	−0.290	−0.379	−0.315	−0.276
	(0.050)[0.000]	(0.040)[0.000]	(0.054)[0.000]	(0.076)[0.000]
δ_7	−0.363	−0.444	−0.394	−0.352
	(0.049)[0.000]	(0.031)[0.000]	(0.048)[0.000]	(0.067)[0.000]
δ_8	−0.411	−0.431	−0.431	−0.413
	(0.046)[0.000]	(0.029)[0.000]	(0.043)[0.000]	(0.063)[0.000]
δ_9	−0.390	−0.465	−0.436	−0.379
	(0.063)[0.000]	(0.039)[0.000]	(0.052)[0.000]	(0.063)[0.000]
δ_{10}	−0.449	−0.548	−0.493	−0.435
	(0.046)[0.000]	(0.028)[0.000]	(0.035)[0.000]	(0.058)[0.000]
ϕ_π	0.322	0.164	–	0.211
	(0.064)[0.000]	(0.015)[0.000]		(0.048)[0.000]
ϕ_μ	0.436	0.529	–	0.504
	(0.035)[0.000]	(0.036)[0.000]		(0.058)[0.000]
φ_π	1.016	0.660	–	0.809
	(0.118)[0.000]	(0.034)[0.000]		(0.069)[0.000]
φ_μ	0.918	1.163	–	0.948
	(0.086)[0.000]	(0.031)[0.000]		(0.082)[0.000]
σ_π	0.320	0.356	0.207	0.307
	(0.050)[0.000]	(0.034)[0.000]	(0.021)[0.000]	(0.067)[0.000]
σ_μ	0.493	0.432	0.290	0.552
	(0.048)[0.000]	(0.032)[0.000]	(0.019)[0.000]	(0.108)[0.000]

Notes: Standard errors in parentheses and p values in brackets. Standard deviations of the transitory and persistent unobservables in the cost of effort function, σ_π and σ_μ, are estimated directly in the specification using normally distributed unobservables and computed from the other parameters for the specifications using the Weibull distribution. Estimates of κ, δ_r for $r = 2, \ldots 10$, ϕ_π and ϕ_μ have been multiplied by 100.

Table 3: MSM parameter estimates.

The first column of Table 3 reports the parameter estimates for the preferred specification, which is based on the sample of 59 Second Movers, assumes Weibull distributed unobservables in the cost of effort function and relies on a diagonal weight matrix. Before discussing the results we briefly consider the goodness of fit of this specification represented by the relevant moments in Table 5 located in Appendix B.3. Table 5 shows that for this specification all simulated moments correspond closely to the values observed in the sample: in particular the observed and simulated moments never differ by more than 1.3 bootstrapped standard deviations.

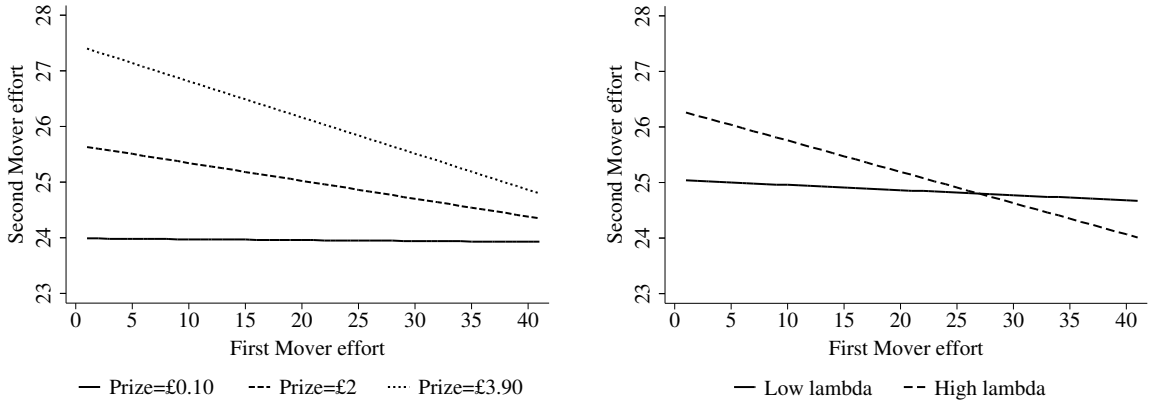
Turning to the parameter estimates for the preferred specification in the first column of Table 3, our estimate of the strength of disappointment aversion on average, $\widetilde{\lambda}_2$, is 1.724 and this is significantly different from zero at all conventional significance levels. In Section 4.4.2 we place this estimate in the context of the related literature but we note here that a figure of 1.724 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 2.9 for 20% of individuals, and is less than 0.5 for 20%. For 11% of individuals, $\lambda_{2,n}$ is less than zero.

The results further show that the cost of effort function exhibits significant convexity, and learning effects work to reduce the convexity of the cost of effort over rounds, leading to higher average effort levels in later rounds. 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. 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).

Next we explore how the disappointment aversion impacts on the effort choices of the Second Movers and in particular look at how Second Movers responds to First Mover effort. Figure 3(a) shows the mean best response of Second Movers with the average value of $\lambda_{2,n}$ to the effort choice of the First Mover.[21] We see strong negative effects of First Mover effort on Second Mover effort at prizes of £2 and £3.90 and essentially no effect at the lowest prize of £0.10. Standard errors, not reported, show that the slope of the reaction function is significantly neg-

[21] Reaction functions were obtained using simulation methods. Specifically, we consider a large number of hypothetical Second Movers, and for each hypothetical Second Mover made draws from the estimated distributions of μ_n and $\pi_{n,r}$ for the preferred specification. Using the estimated parameters of the cost of effort function for round 5, we simulated each hypothetical Second Mover's optimal effort conditional on specific values of First Mover effort and the prize, and computed the mean best response. Reaction functions were obtained by repeating this exercise while varying First Mover effort but holding the prize fixed. Reaction functions are linear and this is a consequence of the quadratic cost of effort function.

ative (at the 1% level) at prizes of £2 and £3.90.[22] Figure 3(b) meanwhile 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. 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, a discouragement effect is observed for Second Movers with high values of $\lambda_{2,n}$, defined to be the 80$^{\text{th}}$ percentile of the distribution of $\lambda_{2,n}$. Standard errors, not reported, show that the slope of the reaction function is significantly negative (at the 1% level) for Second Movers with high values of $\lambda_{2,n}$.



(a) Average lambda.

(b) Prize=£2.

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

Columns 2-4 of Table 3 provide robustness checks for various features of our analysis. We see that irrespective of the choice of sample, the method of weighting the moments and the distributional assumptions imposed on 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. The OWMD and DWMD estimators give similar parameter estimates: thus there is little evidence that using the optimal weight matrix introduces finite sample bias. However we err on the side of caution and do not nominate this as our preferred specification. We also estimate a specification in which the unobservables appearing in the cost of effort function are normally distributed, rather than being drawn from Weibull distributions. While reducing by 2 the number of unknown parameters, the normal distribution is more restrictive than the Weibull, and leads to concave cost of effort functions for subjects with low cost draws.[23] Table 5 shows that using the DWMD estimator with normally distributed unobservables in the cost of effort function fits less well than the preferred specification: the individual moments reveal that the deterioration in fit occurs as this specification does not fit as accurately the distribution of Second Mover efforts. Specifically, the standard deviations of observed and simulated Second Mover efforts differ by

[22]The magnitudes of the estimated slopes are 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.

[23]When estimating the specification with normally distributed unobservables in the cost of effort function we replace $c_{n,r}$ with $\max\{c_{n,r}, 0.0001\}$.

2.3 bootstrapped standard deviations, while the proportions of very low and very high simulated Second Mover efforts are, respectively, 2.8 and 1.8 bootstrapped standard deviations different from the corresponding proportions observed in the sample. Increasing the sample size to 60 Second Movers also leads to a larger discrepancy between the standard deviations of observed and simulated Second Mover efforts than that obtained from the preferred specification.

4.4 Endogenous Reference Points

4.4.1 Evidence

Given that we model disappointment aversion as loss aversion around an agent's endogenous expectation, 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, and no disappointment deficit term appears in the expression for expected utility.

Thus 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.

4.4.2 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 $\lambda > 1$.[24]

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)

[24] Even though their reference point is fixed at the point of optimization, Crawford and Meng (2009) are also unable to separately identify λ and η.

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

$$\frac{1+l_2}{1+g_2} = 1 + \frac{\lambda_2}{1+g_2}. \tag{15}$$

Given an assumption about g_2, our estimate of $\widetilde{\lambda}_2$ therefore implies an estimate of the average value of (15) 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 $\widetilde{\lambda}_2 = 1.724$ implies that $(15) \in (1.862, 2.724)$. This matches previous estimates of the coefficient of loss aversion, and is broadly in line with Crawford and Meng (2009)'s baseline estimate of the ratio of the slopes of total utility in the loss and gain domains of 1.715 in the context of the loss aversion of taxi drivers around rational expectations-based daily income and hours targets which are fixed at the point of optimization.

5 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 reference point given by their expected payoff. A person's reference point is conditioned on her own work effort and that of her rival, and adjusts essentially instantaneously to the effort choices. Disappointment aversion creates a discouragement effect, whereby a competitor slacks off when her rival works hard.

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.

Finally, we believe that the novel real effort slider task we developed for the purposes of this study will prove valuable to researchers running real effort experiments in other settings in which precise quantification of preference and cost parameters is important.

Appendix

A Proofs

A.1 Proof of Proposition 2

Using (1) and (7),

$$EU_2(e_2, e_1) = v\left(\frac{e_2 - e_1 + \gamma}{2\gamma}\right) - \lambda_2 v\left(\frac{\gamma^2 - (e_2 - e_1)^2}{4\gamma^2}\right) - C_2(e_2). \tag{16}$$

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

$$[EU_2(e_{21}^*, e_{11}) - EU_2(e_{22}^*, e_{11})] + [EU_2(e_{22}^*, e_{12}) - EU_2(e_{21}^*, e_{12})] \geq 0. \tag{17}$$

Using (16), we get the following:

$$EU_2(e_{21}^*, e_{11}) - EU_2(e_{21}^*, e_{12}) = v\left(\frac{-e_{11} + e_{12}}{2\gamma}\right) + \lambda_2 v\left(\frac{(e_{21}^* - e_{11})^2 - (e_{21}^* - e_{12})^2}{4\gamma^2}\right); \tag{18}$$

$$EU_2(e_{22}^*, e_{12}) - EU_2(e_{22}^*, e_{11}) = v\left(\frac{-e_{12} + e_{11}}{2\gamma}\right) + \lambda_2 v\left(\frac{(e_{22}^* - e_{12})^2 - (e_{22}^* - e_{11})^2}{4\gamma^2}\right). \tag{19}$$

Thus

$$(17) = \frac{\lambda_2 v}{2\gamma^2}(-e_{21}^* e_{11} + e_{21}^* e_{12} - e_{22}^* e_{12} + e_{22}^* e_{11}) = \frac{\lambda_2 v}{2\gamma^2}(e_{21}^* - e_{22}^*)(e_{12} - e_{11}) < 0 \tag{20}$$

given $\lambda_2 > 0$ for a disappointment averse Second Mover, which contradicts $(17) \geq 0$ 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 (16),

$$\frac{\partial EU_2(e_2, e_1)}{\partial e_2} = \frac{v}{2\gamma} + \frac{\lambda_2 v(e_2 - e_1)}{2\gamma^2} - b - ce_2; \tag{21}$$

$$\frac{\partial^2 EU_2(e_2, e_1)}{\partial e_2^2} = \frac{\lambda_2 v}{2\gamma^2} - c. \tag{22}$$

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:

$$e_2^*(e_1) = \begin{cases} \overline{e} & \text{if } e_1 < \frac{\gamma v + \lambda_2 v\overline{e} - 2\gamma^2(b+c\overline{e})}{\lambda_2 v} \\ \frac{\gamma v - \lambda_2 v e_1 - 2\gamma^2 b}{2\gamma^2 c - \lambda_2 v} \in [0,\overline{e}] & \text{if } e_1 \in \left[\frac{\gamma v + \lambda_2 v\overline{e} - 2\gamma^2(b+c\overline{e})}{\lambda_2 v}, \frac{\gamma v - 2\gamma^2 b}{\lambda_2 v}\right] \\ 0 & \text{if } e_1 > \frac{\gamma v - 2\gamma^2 b}{\lambda_2 v} \end{cases}. \tag{23}$$

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 $e_1 \in [0,\overline{e}]$ 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 (16), $EU_2(e_2^+, e_1) - EU_2(e_2, e_1)$

$$= \frac{v(e_2^+ - e_2)}{2\gamma} + \lambda_2 v\left(\frac{(e_2^+ - e_1)^2 - (e_2 - e_1)^2}{4\gamma^2}\right) - b(e_2^+ - e_2) - \frac{c((e_2^+)^2 - e_2^2)}{2} \tag{24}$$

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

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

$$\breve{e}_1(e_2^+, e_2) = \frac{2\gamma v - 4\gamma^2 b}{2\lambda_2 v} - \left(\frac{2\gamma^2 c - \lambda_2 v}{\lambda_2 v}\right)\left(\frac{e_2^+ + e_2}{2}\right). \tag{26}$$

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

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

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.[25] 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:

$$\lambda_{2,n} = \widetilde{\lambda}_2 + \sigma_\lambda \Phi^{-1}(Q1_{s,n}), \tag{28}$$

   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:

$$\mu_n = \phi_\mu(-\ln(Q2_{s,n}))^{1/\varphi_\mu}; \tag{29}$$

$$\pi_{n,r} = \phi_\pi(-\ln(Q3_{s,n,r}))^{1/\varphi_\pi}. \tag{30}$$

   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.

[25] 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,

$$\sqrt{N}(\widehat{\theta}-\theta) \xrightarrow{d} N\left(0, \frac{S+1}{S}\left(D'WD\right)^{-1} D'W\Omega WD\left(D'WD\right)^{-1}\right) \quad \text{as} \quad N\to\infty, \tag{31}$$

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

$$D = \frac{1}{S}\sum_{s=1}^{S}\left.\frac{dM_s(\theta_t)}{d\theta_t'}\right|_{\theta_t=\theta}. \tag{32}$$

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 5000 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
SD($e_{2,n,r}$)	Standard deviation of Second Mover effort	ϕ_π,ϕ_μ,φ_π,φ_μ,σ_λ
Prop($e_{2,n,r}$<15); Prop($e_{2,n,r}$>35)	Proportions of Second Mover efforts below 15 and above 35	ϕ_π,ϕ_μ,φ_π,φ_μ,σ_λ
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
Corr($e_{2,n,r}, e_{2,n,r-1}$); Corr($e_{2,n,r}, e_{2,n,r-2}$)	1st and 2nd order autocorrelations in Second Mover effort	ϕ_μ,φ_μ,σ_λ
Mean($e_{2,n,r}$) for $r = 1, \ldots, 10$	Round specific means of Second Mover effort	b, δ_r for $r = 2, \ldots, 10$
Corr($e_{2,n,r}, v_{n,r} \mid e_{1,n,r}, e_{1,n,r}v_{n,r}, RD, SE$)	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
Corr($e_{2,n,r}, e_{1,n,r} \mid v_{n,r}, e_{1,n,r}v_{n,r}, RD, SE$)	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	$\widetilde{\lambda}_2$
Corr($e_{2,n,r}, v_{n,r}e_{1,n,r} \mid e_{1,n,r}, v_{n,r}, RD, SE$)	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	$\widetilde{\lambda}_2$
Pc$_j$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	ϕ_π,ϕ_μ,φ_π,φ_μ
Pc$_j$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
Pc$_j$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
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, $\widetilde{\lambda}_2$
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, $\widetilde{\lambda}_2$
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, $\widetilde{\lambda}_2$
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, SE 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.

	59 Second Movers					60 Second Movers		
	Sample Moment	Bootstrapped SD	DWMD Weibull Costs	OWMD Weibull Costs	DWMD Normal Costs	Sample Moment	Bootstrapped SD	DWMD Weibull Costs
$\text{SD}(e_{2,n,r})$	5.875	0.508	5.540	5.165	4.695	6.649	0.810	5.742
$\text{Corr}(e_{2,n,r}, e_{2,n,r-1})$	0.652	0.061	0.638	0.663	0.653	0.735	0.081	0.706
$\text{Corr}(e_{2,n,r}, e_{2,n,r-2})$	0.596	0.084	0.612	0.644	0.621	0.693	0.102	0.697
$\text{SD}(e_{2,n,r} - e_{2,n,r-1})$	4.828	0.724	4.661	4.169	3.839	4.788	0.731	4.353
$\text{Mean}(e_{2,n,1})$	21.763	0.779	21.730	21.669	21.536	21.400	0.839	21.488
$\text{Mean}(e_{2,n,2})$	23.458	0.626	23.380	23.567	23.190	23.067	0.725	23.242
$\text{Mean}(e_{2,n,3})$	24.831	0.631	24.688	24.896	24.740	24.417	0.735	24.792
$\text{Mean}(e_{2,n,4})$	25.203	0.573	25.190	24.989	25.045	24.783	0.710	24.772
$\text{Mean}(e_{2,n,5})$	25.119	0.730	25.182	25.727	25.045	24.700	0.818	24.488
$\text{Mean}(e_{2,n,6})$	24.898	0.895	24.642	25.356	24.685	24.483	0.964	24.217
$\text{Mean}(e_{2,n,7})$	25.763	0.793	25.641	26.224	25.655	25.333	0.873	25.269
$\text{Mean}(e_{2,n,8})$	26.169	0.658	26.189	25.989	26.142	25.733	0.789	26.009
$\text{Mean}(e_{2,n,9})$	26.254	0.852	25.991	26.472	26.114	25.817	0.944	25.477
$\text{Mean}(e_{2,n,10})$	26.729	0.764	26.460	27.280	26.793	26.283	0.863	26.292
$\text{Corr}(e_{2,n,r}, v_{n,r} \mid e_{1,n,r}, e_{1,n,r}v_{n,r}, RD, SE)$	0.124	0.044	0.082	0.084	0.081	0.124	0.043	0.078
$\text{Corr}(e_{2,n,r}, e_{1,n,r} \mid v_{n,r}, e_{1,n,r}v_{n,r}, RD, SE)$	0.041	0.042	0.002	0.001	-0.001	0.044	0.041	-0.001
$\text{Corr}(e_{2,n,r}, v_{n,r}e_{1,n,r} \mid e_{1,n,r}, v_{n,r}, RD, SE)$	-0.095	0.048	-0.036	-0.034	-0.035	-0.096	0.046	-0.035
$\text{Pc}_{17}\text{Corr}_n(e_{2,n,r}, v_{n,r} \mid e_{1,n,r}, e_{1,n,r}v_{n,r}, RT)$	-0.275	0.097	-0.171	-0.143	-0.172	-0.275	0.095	-0.160
$\text{Pc}_{33}\text{Corr}_n(e_{2,n,r}, v_{n,r} \mid e_{1,n,r}, e_{1,n,r}v_{n,r}, RT)$	0.033	0.080	0.048	0.081	0.027	0.033	0.082	0.040
$\text{Pc}_{50}\text{Corr}_n(e_{2,n,r}, v_{n,r} \mid e_{1,n,r}, e_{1,n,r}v_{n,r}, RT)$	0.222	0.072	0.222	0.256	0.207	0.222	0.073	0.209
$\text{Pc}_{66}\text{Corr}_n(e_{2,n,r}, v_{n,r} \mid e_{1,n,r}, e_{1,n,r}v_{n,r}, RT)$	0.388	0.041	0.353	0.394	0.363	0.403	0.037	0.372
$\text{Pc}_{83}\text{Corr}_n(e_{2,n,r}, v_{n,r} \mid e_{1,n,r}, e_{1,n,r}v_{n,r}, RT)$	0.469	0.051	0.525	0.556	0.513	0.504	0.057	0.544
$\text{Pc}_{17}\text{Corr}_n(e_{2,n,r}, e_{1,n,r} \mid v_{n,r}, e_{1,n,r}v_{n,r}, RT)$	-0.328	0.052	-0.389	-0.383	-0.393	-0.328	0.051	-0.413
$\text{Pc}_{33}\text{Corr}_n(e_{2,n,r}, e_{1,n,r} \mid v_{n,r}, e_{1,n,r}v_{n,r}, RT)$	-0.218	0.060	-0.207	-0.204	-0.191	-0.218	0.061	-0.222
$\text{Pc}_{50}\text{Corr}_n(e_{2,n,r}, e_{1,n,r} \mid v_{n,r}, e_{1,n,r}v_{n,r}, RT)$	0.019	0.090	-0.024	-0.031	-0.014	0.019	0.092	-0.045
$\text{Pc}_{66}\text{Corr}_n(e_{2,n,r}, e_{1,n,r} \mid v_{n,r}, e_{1,n,r}v_{n,r}, RT)$	0.179	0.064	0.140	0.138	0.151	0.193	0.064	0.130
$\text{Pc}_{83}\text{Corr}_n(e_{2,n,r}, e_{1,n,r} \mid v_{n,r}, e_{1,n,r}v_{n,r}, RT)$	0.361	0.064	0.341	0.343	0.344	0.387	0.068	0.365
$\text{Pc}_{17}\text{Corr}_n(e_{2,n,r}, v_{n,r}e_{1,n,r} \mid e_{1,n,r}, v_{n,r}, RT)$	-0.194	0.079	-0.215	-0.170	-0.212	-0.194	0.077	-0.229
$\text{Pc}_{33}\text{Corr}_n(e_{2,n,r}, v_{n,r}e_{1,n,r} \mid e_{1,n,r}, v_{n,r}, RT)$	0.019	0.065	0.005	0.031	-0.012	0.019	0.066	-0.006
$\text{Pc}_{50}\text{Corr}_n(e_{2,n,r}, v_{n,r}e_{1,n,r} \mid e_{1,n,r}, v_{n,r}, RT)$	0.146	0.057	0.169	0.199	0.159	0.146	0.058	0.158
$\text{Pc}_{66}\text{Corr}_n(e_{2,n,r}, v_{n,r}e_{1,n,r} \mid e_{1,n,r}, v_{n,r}, RT)$	0.298	0.068	0.312	0.338	0.312	0.331	0.068	0.331
$\text{Pc}_{83}\text{Corr}_n(e_{2,n,r}, v_{n,r}e_{1,n,r} \mid e_{1,n,r}, v_{n,r}, RT)$	0.474	0.050	0.489	0.506	0.483	0.523	0.051	0.501
$\text{Mean}(e_{2,n,r} \mid e_{1,n,r}<23 \cap v_{n,r}<1.33)$	23.821	0.856	23.958	24.304	24.075	23.821	0.849	23.790
$\text{Mean}(e_{2,n,r} \mid e_{1,n,r}<23 \cap v_{n,r}>2.55)$	25.485	0.805	25.441	25.625	25.481	25.485	0.799	25.209
$\text{Mean}(e_{2,n,r} \mid e_{1,n,r}>28 \cap v_{n,r}<1.33)$	25.836	0.966	25.070	25.504	25.160	25.016	1.256	24.607
$\text{Mean}(e_{2,n,r} \mid e_{1,n,r}>28 \cap v_{n,r}>2.55)$	25.050	1.210	25.488	25.808	25.431	24.439	1.284	25.071
$\text{Prop}(e_{2,n,r} < 15)$	0.029	0.010	0.032	0.018	0.000	0.045	0.019	0.047
$\text{Prop}(e_{2,n,r} > 35)$	0.015	0.008	0.018	0.012	0.029	0.015	0.008	0.015
χ^2 Statistic (p. value)			56.246 (0.000)	19.377 (0.561)	107.466 (0.000)			88.068 (0.000)

Notes: See Table 4 for a description of the moments. Observed moments are computed from the sample and simulated moments are computed using the DWMD and OWMD parameter estimates.

Table 5: Goodness of fit.

C Experimental Instructions

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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