Social Comparisons in Peer Effects*

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Abstract

Even without material incentives for coordination or learning, previous studies demonstrate the importance of social interactions in individual decision making. However, identifying why conformity arises absent explicit incentives faces the challenge that rationalizing theories must rely on unobservable preferences or beliefs. Therefore, empirical distinction requires theories that make falsifiable predictions beyond the basic dynamic of conformity. To that end, we propose a model of self signaling in peer effects in which individuals rely on their own choices along with social comparisons to form their self image. This approach makes novel predictions on peer selection, i.e. how one determines which peers do or do not provide information relevant to one's own choices, and on how an individual will condition their choices in anticipation of social information. These predictions are tested in a series of real-effort lab experiments.

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1 Introduction

The importance of social information in individual decision making is well documented. Not only do individuals learn from their peers when making decisions over new and unfamiliar opportunities (Foster and Rosenzweig, 1995; Duflo and Saez, 2002; Bursztyn et al., 2014; Dahl et al., 2014), but they also converge to behavioral conformity in the work place (Mas and Moretti, 2009; Bandiera et al., 2010) and in the classroom (Hoxby, 2000; Sacerdote, 2001; Zimmerman, 2003; Bursztyn et al., 2017). While material incentives for coordination or reliance on social information for uncertainty resolution can explain some instances of social conformity (Katz and Shapiro, 1986; Banerjee, 1992; Foster and Rosenzweig, 1995), previous research demonstrates the importance of social influence that is not predicted by neo-classical theories (Frey and Meier, 2004; Falk and Ichino, 2006; Goette et al., 2006; Alpizar et al., 2008; Mas and Moretti, 2009; Shang and Croson, 2009; Chen et al., 2010).

A common explanation for social conformity, absent material incentives, is adherence to social norms. Such theories are typically driven by imposing sanctions on deviating from a predetermined action (Akerlof, 1980; Jones, 1984; Akerlof and Kranton, 2000) or by individuals pooling at a common action to signal an optimal social type (Bernheim, 1994).[1] However, distinguishing between plausible explanations for conformity without explicit incentives faces a natural challenge. If incentives are unobservable, a rationalizing theory will necessarily rely on unobservable preferences or beliefs. Therefore, theories of peer effects are empirically distinguishable only if they differ in their predictions beyond the basic dynamic of conformity begetting conformity.

In this project we propose and experimentally test a theory of (partial) social conformity in the absence of a socially optimal action. Building on Bénabou and Tirole (2006), our theory produces novel predictions on how decision makers differentiate between peer behavior that is relevant or irrelevant to their own decisions. Further, we introduce a theoretical foundation and experimental test for self image as a mechanism underlying peer effects.

Our theory posits that individuals have an intrinsic desire to judge and evaluate themselves. That is, each person would like to perceive himself positively – e.g. diligent, intelligent, charitable, et cetera. However, individuals often lack a direct or objective means of self evaluation. Instead, they rely on their history of actions as a noisy signal of their attributes. This theory requires no predetermined socially optimal action. Rather, self-image is increasing in the performance of a costly action. Under these assumptions an individual faces intrinsic incentives to manipulate his personal image through his actions. Further, signal extraction is improved when he observes others performing similar tasks – i.e. social comparisons allow him to better understand the image implications of his own choices.

In the context of this signal extraction, we prove that if self image is decreasing in the observation of more costly peer-choice, then diminishing marginal utility over self image will produce positive peer effects. The intuition behind this result is simple. For example, consider a group of employees working on an unfamiliar task under a fixed-wage spot contract that offers no incentives for collusion on effort[2]. Why would an employee condition his own output on the observed output of a peer? Suppose that each employee wishes to perceive

[1] Bernheim and Exley (2015) explore an alternative explanation for social conformity that establishes preference mechanisms that drive instances of social conformity. Our project explores a belief mechanism.

[2] Previous experiments have documented peer effects under such conditions (Falk and Ichino, 2006)

himself as hard-working but is unsure how to judge his performance due to lack of experience. If each employee draws comparisons with peer output to better understand whether his output suggests diligence or laziness, then our theory establishes that a group of employees will conform in output when each individual is more afraid to learn that he is the laziest group member than he is eager to demonstrate that he is the most diligent.

Modeling social comparisons as self signaling also offers novel predictions on the determination of peer groups. Differential responsiveness to peer behavior is mediated by how informative observed behavior is to one's self image. The signal a peer's choice provides is refined in the similarity of a task's incentives and costs. Dissimilarity in peer environments acts as signal interference and diminishes behavioral convergence. For example, suppose an individual observes that his coworkers are donating some proportion of their holiday bonuses to charity. Then he will feel less compelled to donate to charity himself if he suspects that he received a smaller bonus than most of his colleagues.

The experiments in this project test our theory's predictions on self signaling produced conformity and peer-group formation. The first experiment uses model predictions to test the relevance of self-image signal extraction in peer effects. In this experiment we test whether individuals are more willing to do a costly task in exchange for charitable donations if they anticipate learning how their decisions compare to the decisions of previous participants. Importantly, all participants commit to how many tasks they are willing to complete prior to learning any information on how their decisions compare to the decisions of others. Furthermore, both those who will and will not be shown the distribution of others' decisions must predict where their decision lies in the distribution of all previous choices. By drawing attention to the full set of information that the experimenter has in both treatment and baseline we ensure that any treatment effect is driven not by experimenter demand but by the anticipation of learning how one's decision compares to the decisions of others. In accordance with our theory's predictions we find that participants are willing to do more tasks when they know they will learn the distribution of previous participant choices than when they know they will remain uninformed.

The second experiment tests whether a noisier signal mitigates peer effects by statistically garbling the information peer behavior provides. Documenting that decision makers are less responsive to statistically garbled signals is an important result of this project. Our theory relies on individuals using peer behavior as part of a signal extraction to better understand the image implications of their own choices. Further, it posits that dissimilarity in the incentives and costs that decision makers face will cloud what one decision maker can learn from an other's choices – thereby reducing conformity in behavior. However, for this theory to be plausible the basic dynamics of signal extraction must hold. Our second experiment demonstrates that participants are highly sensitive to the receipt of a statistically refined signal and unresponsive to a fully garbled signal. This presents a natural test for the signal extraction hypothesis, and our results lay the foundation for further investigation of what environmental factors produce signal interference in more natural decision making settings.

The economic scope of peer influence is vast. Previous work has documented that people's uptake of retirement savings programs, effort at work, decisions to invest in financial instruments, and participation in paternal leave are causally related to the observed decisions of their peers (Duflo and Saez, 2002; Mas and Moretti, 2009; Bandiera et al., 2010; Bursztyn et al., 2014; Dahl et al., 2014), and that students' academic achievements covary with those whom they share a classroom or dormitory (Hoxby, 2000; Sacerdote, 2001; Zimmerman, 2003). A careful investigation of how self-signaling and social comparisons may drive social conformity could not only contribute to our understanding of the existing empirical and theoretical literature, but also provide researchers and policy makers with greater predictive power over when peer effects are likely to exist in unexplored environments.

Section 2 presents our model of social comparisons and explains the formal intuition behind our results. Section 3 details our experimental design, and section 4 discusses the results of our experiment. Finally, 5 concludes and discusses possible future work on this topic.

2 A Theory of Social Comparisons

By modeling social comparisons as self signaling this project delivers three principal theoretical contributions. In section 2.2 we show that if an individual experiences positive image returns in the performance of a costly action and negative image returns in the observation of higher peer performance, then diminishing marginal utility over self image will produce convergence in group behavior. Section 2.3 shows that responsiveness to peer behavior is mediated by how informative the behavior of others is to one's own image. Further, we find that the signal provided by others' choices is refined in the similarity of extrinsic costs faced by the decision makers. Finally, section 2.4 shows that self signaling will induce decision makers to choose more costly actions in anticipation of learning where their choice lies in the distribution of others' choices. This prediction is used to experimentally disentangle self and social image. We first set up the decision maker's problem in section 2.1.

2.1 Preliminaries

Let agent 1 choose an activity level $a_1 \in \mathbb{R}_+$. Further suppose that a_1 incurs cost $C(a_1, \omega_1 - \theta_1)$ and yields image utility $U(a_1)$. Here we define θ_1 as agent 1's level of ability and ω_1 as the extrinsic difficulty of the task. θ_1 and ω_1 are random variables. Cost is increasing in a_1, $\frac{\partial C}{\partial a_1} > 0$, and marginal cost is decreasing in one's ability and increasing in extrinsic task difficulty, $\frac{\partial^2 C}{\partial a_1 \partial \theta_1} = -\frac{\partial^2 C}{\partial a_1 \partial \omega_1} < 0$. That is, agent 1 trades of task cost and image utility to solve:

$$max_{a_1} U(a_1) - C(a_1, \omega_1 - \theta_1) \tag{1}$$

The interpretation of $C(a_1, \omega_1 - \theta_1)$ is straightforward; given a_1, the agent experiences task completion cost $C(a_1, \omega_1 - \theta_1)$.[3] For example, if a_1 is a charitable gift, then the cost of giving is increasing in the size of the gift. Further, the marginal utility loss of giving is increasing in the financial hardship it imposes on agent 1 – ω_1 – but decreasing in agent 1's personal altruism – θ_1.

[3]For notational simplicity we define the cost function $C(a, \omega - \theta)$ to be the negative net utility, apart from image returns, of taking action a under parameters ω and θ. As such, we can more generally interpret ω_1 and θ_1 as any environmental factor and any personal characteristic that mediate direct utility.

We introduce self-image signal extraction into this problem by defining image utility as $U(a_1) = V(E[\theta_1|a_1])$. Where V is a strictly increasing function. Here, we assume that agent 1 does not observe ω_1 independently of θ_1. Rather, agent 1 knows V and the distributions of θ_1 and ω_1. This allows $U(a_1)$ to be a known function. Specifically, $U(a_1)$ is the utility that assumes any observed a_1 is the solution to the first order condition:

$$V'(E[\theta_1|a_1])\frac{\partial E[\theta_1|a_1]}{\partial a_1} = \frac{\partial C}{\partial a_1}(a_1, \omega_1 - \theta_1) \tag{2}$$

Since this assumption is necessarily true in equilibrium, for all optimal $a_1^* = argmax_{a_1} U(a_1) - C(a_1, \omega_1 - \theta_1)$ the decision maker implicitly observes $\omega_1 - \theta_1$. We then define self image to to be expectation over one's ability parameter given one's level of activity – $E[\theta_1|a_1^*]$. $U(a_1^*) = V(E[\theta_1|a_1^*])$ is the utility experienced over image $E[\theta_1|a_1]$. Note that when the decision maker is being observed by others U may serve as both a self and social image function.[4]

In the context of charitable giving, our model states that altruism – θ_1 – cannot be measured directly. Instead agent 1 relies on his choice – a_1 – as a signal of his altruism. This signal is noisy because altruism alone does not determine his donation. After all, the decision to give not only indicates the desire to give, but also the financial ability to give – ω_1. Therefore, his donation is a joint signal of his altruism and extrinsic motivations such as wealth, tax incentives, and uncertainty of future income – a_1 becomes a signal of $\omega_1 - \theta_1$. Having observed this joint signal, agent 1 forms self image equal to the expected value of his altruism, $E[\theta|a_1] = E[\theta_1|\omega_1 - \theta_1]$, and experiences image utility $V(E[\theta|a_1])$.

Next, we introduce the observation of a second agent's action – a_2 – into agent 1's decision problem.[5]

$$max_{a_1} U(a_1, a_2) - C(a_1, \omega_1 - \theta_1) \tag{3}$$

Note that this model make endogenous the desire to condition one's own decision on the decisions of others. To see this consider the first order condition of the above optimization problem:

$$\frac{\partial U}{\partial a_1}(a_1, a_2) = \frac{\partial C}{\partial a_1}(a_1, \omega_1 - \theta_1) \tag{4}$$

Similar to the case of no social information, U is a known function that must be consistent with the signal extraction of $E[\theta_1|a_1, a_2]$. Therefore, U is endogenously defined to satisfy first order condition 4. As such, person 1 will condition a_1 on person 2's decision a_2 only if V, C, and the distributions of (θ_1, θ_2) and (ω_1, ω_2) result in a signal extraction of $E[\theta_1|a_1, a_2]$ and image utility function $U(a_1, a_2) = V(E[\theta_1|a_1, a_2])$ that predicts optimal a_1^* changes with observed a_2. Note that this utility function does not adhere to an exogenously defined

[4] As per Bénabou and Tirole (2006), in order to close this model of self image we must also assume that the decision maker suffers imperfect recall. That is, the decision maker may be able to remember the action – a_1 – he took, but will not be able to recall intangible influences. Otherwise the decision maker could simply recall the marginal cost of doing one task. Therefore, the current self optimizes equation 1 with respect to the future self's inferred expectation of θ_1 given the observed a_1.

[5] For simplicity, we will assume that agent 2 does not observe a_1.

optimal action or social type. Rather, we will derive conditions on the strictly increasing image utility and cost functions, V and C, and the joint distribution of (ω_1, ω_2) that predict convergent behavior.

2.2 The Coefficient of Peer Effects

We first establish the basic dynamics of the single decision maker who does not observe other's choices. Recall that this agent solves equation 1 with first order equation 2. Rewrite the first order equation as $F(X,Y) = 0$ where $X = a_1$ and $Y = (\theta_1, \omega_1)$. Further, define $G(Y)$ such that $F(G(Y), Y) = 0$ for all Y. Then by the implicit function theorem, we know that $G'(Y) = -A_x^{-1} A_y$ where $A_x = F_X(X,Y)$ and $A_y = F_Y(X,Y)$. From equation 2 we get $A_x = \left[\frac{\partial F}{\partial a_1}\right]$ and $A_y = \left[\frac{\partial F}{\partial \theta_1}\ \frac{\partial F}{\partial \omega_1}\right]$. Notice that, by definition, $G(Y)$ is the optimal action, a_1^*, given a realization of (θ_1, ω_1). This delivers the following lemma.

Lemma 1. *Suppose that agent 1 solves for:*

$$a_1^* = argmax_{a_1} \phi U(a_1) - C(a_1, \omega_1 - \theta_1)$$

Which has first order condition:

$$\phi \frac{\partial U}{\partial a_1}(a_1) - \frac{\partial C}{\partial a_1}(a_1, \omega_1 - \theta_1) = 0$$

If $\frac{\partial E[\theta_1|\omega_1 - \theta_1]}{\partial(\omega_1 - \theta_1)} < 0$, $\frac{\partial^2 C}{\partial a_1 \partial(\omega - \theta_1)}(a_1, \omega_1 - \theta_1) > 0$ *and* $\frac{\partial^2 C}{\partial a_1^2}(a_1, \omega - \theta_1) \geq 0$, *then* $\frac{\partial a_1^*}{\partial \theta_1} = -\frac{\partial a_1^*}{\partial \omega_1} > 0$.

Lemma 1 simply states that if the marginal cost of a_1 is non-decreasing in a_1 and increasing in the difference between task difficulty and agent 1's ability, $\omega_1 - \theta_1$, then the optimal choice of a_1 will be increasing in agent 1's ability and decreasing in task difficulty so long as the conditional expectation of θ_1 is decreasing in $\omega_1 - \theta_1$. In the context of our example, this states that charitable giving increases in the decision maker's altruism and prosperity.

We now move to the case where agent 1 observes the actions of all other agents $i \in \{2, \ldots, N\}$. For simplicity we assume that all agents $i > 1$ have already made their decisions and cannot observe a_1. Now there are N equations to solve:[6]

$$max_{a_1} \phi U(a_1, a_2, \ldots, a_N) - C(a_1, \omega_1 - \theta_1)$$

$$max_{a_1} \phi U(a_2) - C(a_2, \omega_2 - \theta_2)$$

$$\vdots$$

$$max_{a_N} \phi U(a_N) - C(a_N, \omega_N - \theta_N)$$

This results in the first order conditions:

[6] In this case we assume that the first N movers ignore the consequences of their actions on the second mover's action since they will not observe the second mover's action.

$$\phi \frac{\partial U}{\partial a_1}(a_1, a_2, \ldots, a_N) - \frac{\partial C}{\partial a_1}(a_1, \omega_1 - \theta_1) = 0$$

$$\phi \frac{\partial U}{\partial a_2}(a_2) - \frac{\partial C}{\partial a_2}(a_1, \omega_1 - \theta_1) = 0$$

$$\vdots$$

$$\phi \frac{\partial U}{\partial a_N}(a_N) - \frac{\partial C}{\partial a_N}(a_N, \omega_N - \theta_N) = 0$$

We again apply the implicit function theorem, now to this system of equations.[7] This yields proposition 1.

Proposition 1. *Define* $a_1^* = argmax_{a_1} \phi U(a_1, a_2, \ldots, a_N) - C(a_1, \omega_1 - \theta_1)$. *Then, for all* $i \in \{2, \ldots, N\}$

$$\frac{\partial a_1^*}{\partial a_i} = \frac{-V''\left(E[\theta_1|a_1, a_i]\right) \frac{\partial E[\theta_1|a_1,a_i]}{\partial a_i}}{V''\left(E[\theta_1|a_1, a_i]\right) \frac{\partial E[\theta_1|a_1,a_i]}{\partial a_1} - \frac{\partial^2 C}{\partial a_1^2}(a_1, \omega_1 - \theta_1)}$$

Proposition 1 states how individuals condition their action on the observed action of an other person.[8] That is, if $\frac{\partial E[\theta_1|a_1,a_i]}{\partial a_1} > 0$, $\frac{\partial E[\theta_1|a_1,a_i]}{\partial a_i} < 0$, $V''\left(E[\theta_1|a_1, a_i]\right) < 0$, and $\frac{\partial^2 C}{\partial a_1^2}(a_1, \omega - \theta_1) \geq 0$, then $\frac{\partial a_1^*}{\partial a_i} > 0$. Further, if $\frac{\partial E[\theta_1|a_1,a_i]}{\partial a_1} \geq -\frac{\partial E[\theta_1|a_1,a_i]}{\partial a_i}$, then $\frac{\partial a_1^*}{\partial a_i} \leq 1$. In other words, if the expectation of one's own θ is increasing in one's own action and decreasing in an other's action, then we will observe positive peer effects if and only if the image utility function, V, is concave. Further, we find that the degree of conformity is mediated by the convexity of costs and concavity of image utility.

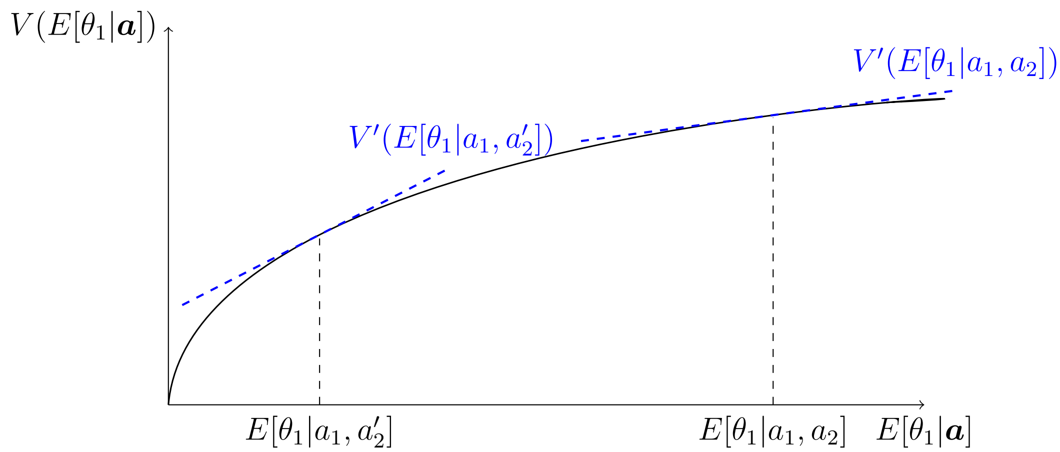
The geometric intuition behind our first result is shown in shown in figure 1. Let $a_2' > a_2$, and, for simplicity, assume that $\frac{\partial^2 E[\theta_1|a_1,a_2]}{\partial a_1 \partial a_2} = \frac{\partial^2 E[\theta_1|a_1,a_2]}{\partial a_1^2} = 0$. Under these conditions we have that $V'(E[\theta_1|a_1, a_2'])\frac{\partial E[\theta_1|a_1,a_2']}{\partial a_1} > V'(E[\theta_1|a_1, a_2])\frac{\partial E[\theta_1|a_1,a_2]}{\partial a_1}$ for all a_1 due to the strict concavity of V. Therefore, since the cost function $C(a_1, \omega_1 - \theta_1)$ is not dependent on a_2, we have that $argmax_{a_1} U(E[\theta_1|a_1, a_2']) - C_1(a_1, \omega_1 - \theta_1) > argmax_{a_1} U(E[\theta_1|a_1, a_2]) - C_1(a_1, \omega_1 - \theta_1)$. In other words, person 1 chooses more costly a_1 in response to a more costly choice of a_2 because the marginal image utility of activity at $E[\theta_1|a_1, a_2']$ is higher than the marginal image utility at $E[\theta_1|a_1, a_2]$.

2.3 Peer Selection

Proposition 1 allows us to differentiate between peers who do and do not provide relevant social information. Specifically, it tells us that, given two observed choices a_i and a_j, $\frac{\partial a_1^*}{\partial a_i} >$

[7] See theoretical appendix section A.2.1.

[8] Interestingly, the expression is invariant across unilateral and bilateral observation. That is, ignoring reflection effects, proposition 1 describes how a_1^* responds to a_2 when person 1 observes a_2 and person 2 *does not* observe a_1 and when person 1 observes a_2 and person 2 *does* observe a_1



Notes: Here $E[\theta_1|a_1, a_2]$ is the image obtained by person 1 after having performed action a_1 and having observed action a_2. $V(E[\theta_1|a_1, a_2])$ is the utility that person 1 experiences over $E[\theta_1|a_1, a_2]$. We assume that $a_2' > a_2$.

Figure 1: Concavity Induced Peer Effects

$\frac{\partial a_1^*}{\partial a_j}$ if $\frac{\partial E[\theta_1|a_1,a_2,\ldots,a_N]}{\partial a_i} < \frac{\partial E[\theta_1|a_1,a_2,\ldots,a_N]}{\partial a_j}$. In other words, agent 1 will most responsive to the choices of those whose decisions are most informative to his own personal image. To see why, we refer back to figure 1. Again, consider a_1, a_2, and a_2' such that $a_2' > a_2$. Since, V is strictly concave, we see that $V'(E[\theta_1|a_1, a_2']) - V'(E[\theta_1|a_1, a_2])$ increases in $E[\theta_1|a_1, a_2] - E[\theta_1|a_1, a_2']$. That is, the more an increase in a_2 depresses agent 1's self image, the higher the marginal utility of activity for agent 1. Again, since agent 1's marginal cost is not dependent of agent 2's choice, this induces agent 1 to choose higher a_1.

The following corollaries find that informativeness of peer choice is mediated by the perceived similarity of explicit costs and incentives.[9]:

Corollary 1. *Suppose that for* $i \in \{1, 2\}$, $\theta_i \sim \mathcal{N}(\mu_\theta, \sigma_\theta)$ *and that* $cov(\theta_1, \theta_2) = 0$. *Further, let* $(\omega_1, \omega_2) \sim \mathcal{N}(\boldsymbol{\mu_\omega}, \boldsymbol{\Sigma_\omega})$. *Then* $\frac{\partial a_1^*}{\partial a_2}$ *in increasing in* $cov(\omega_1, \omega_2)$.

Corollary 2. *Suppose that for* $i \in \{1, 2, 3\}$, $\theta_i \sim \mathcal{N}(\mu_\theta, \sigma_\theta)$ *and that for* $i \neq j$, $cov(\theta_i, \theta_j) = 0$. *Further, let* $(\omega_1, \omega_2, \omega_3) \sim \mathcal{N}(\boldsymbol{\mu_\omega}, \boldsymbol{\Sigma_\omega})$. *Then* $\frac{\partial a_1^*}{\partial a_2} > \frac{\partial a_1^*}{\partial a_3}$ *if and only if* $cov(\omega_1, \omega_2) > cov(\omega_1, \omega_3)$.

Corollary 1 states that the signal an other's action provides is refined in the covariance of agent 1 and 2's cost parameters. The intuition behind this result is simple. Suppose agents 1 and 2 donate a_1 and a_2 to charity. Then if their financial ability to give is known to be identical – i.e. $\omega_1 = \omega_2$ – then any difference in a_1 and a_2 must be due to differentiated desires to give. Similarly, corollary 2 states that agent 1 will be most responsive to choices of those who share the most similar extrinsic costs. That is, our model predicts that a charitable donation campaign should inform prospective donors of the generosity of others in similar financial positions. For example, a mail or door-to-door campaign should mention the gifts of others in who live in the same neighborhood.

[9] Proofs found in appendix section A.2.2

2.4 Anticipation of Social Information

Our final result establishes the anticipation effect of self signaling. We change notation for this analysis. Let a_s be one's chosen action and let $n \leq N$ be the rank of one's action out of a population of N persons who each choose their own action a. That is, a_s is of rank n if and only if $n-1$ persons chose an action smaller than a_s and $N-n-1$ persons chose an action higher than a_s. For simplicity, we assume that equality with a_s is not possible.

Now suppose that the decision maker knows that he will not learn his rank n. Then even if he considers what his expected rank n is, he will choose a_s^* according to the usual first order condition.

$$max_{a_s} \phi U\left(E\left[E\left[\theta_s | a_s, E[n|a_s]\right]|a_s\right]\right) - C(a_s, \omega - \theta_s)$$
$$= max_{a_s} \phi U\left(E\left[\theta_s|a_s\right]\right) - C(a_s, \omega - \theta_s)$$

With first order condition

$$V'\left(E\left[\theta_s|a_s\right]\right)\frac{\partial E\left[\theta_s|a_s\right]}{\partial a_s} = \frac{\partial C}{\partial a_s}(a_s, \omega - \theta_s) \tag{5}$$

This imposes that the decision maker optimizes over $E\left[E\left[\theta_s|a_s, \sum_{n=1}^{N} P_n(a_s) * n\right]|a_s\right] = E\left[\theta_s|a_s\right]$ since a_s is the only information he will obtain. However, if he knows that we will learn his true relative rank, he solves

$$max_{a_s}\sum_{n=1}^{N} P_n(a_s) * V\left(E\left[\theta_s|a_s, n\right]\right) - C(a_s, \omega - \theta_s)$$

.

With first order condition

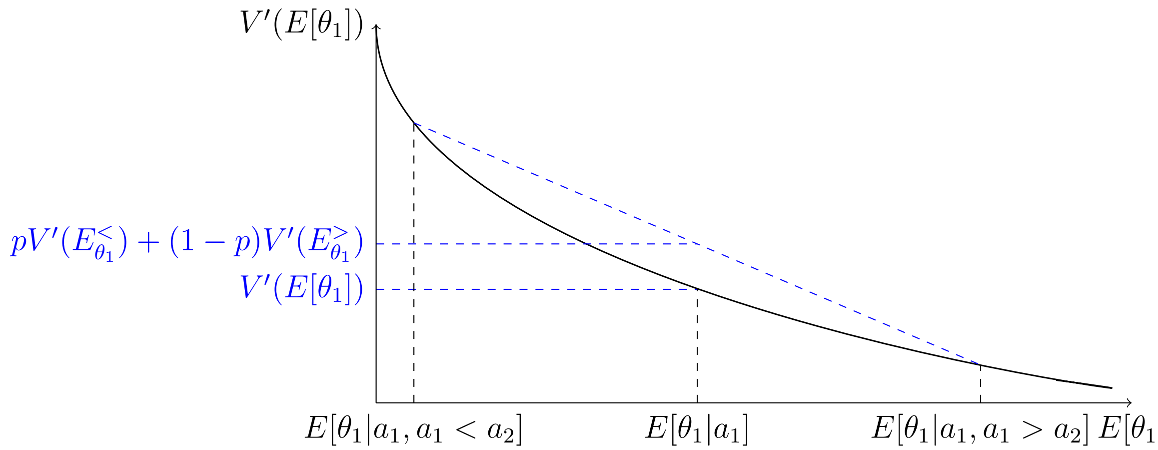
$$\sum_{n=1}^{N} P_n(a_s) * V'\left(E\left[\theta_s|a_s, n\right]\right)\frac{\partial E\left[\theta_s|a_s, n\right]}{\partial a_s} + \sum_{n=1}^{N} P_n'(a_s) V\left(E\left[\theta_s|a_s, n\right]\right) = \frac{\partial C}{\partial a_s}(a_s, \omega - \theta_s) \tag{6}$$

In the appendix we demonstrate that convexity of marginal image utility implies that left hand side of equation 6 is larger than the left hand side of equation 5 for all a_s[10]. That is, we show that marginal image utility greater when the decision maker anticipates learning his place in the distribution of other's choices. The intuition is that the marginal dis-utility of performing below expectation will be greater than the marginal utility of performing above expectation. As such, an individual will exert more effort in order to hedge against bad news.

The mechanism behind this result is illustrated in figure 2. Figure 2 plots marginal utility on the y-axis and image on the x-axis. Assume there are only two decision makers. $E[\theta_1|a_1, a_1 < a_2]$ is agent 1's image if he learns $a_1 < a_2$. Similarly, $E[\theta_1|a_1, a_1 > a_2]$ is agent 1's image if he learns that agent 2 chose a less costly action. For the sake of this

[10] Found in section A.2.3

example, assume that $E[\theta_1|a_1, a_1 < a_2] < Pr(a_1 < a_2|a_1)E[\theta_1|a_1, a_1 < a_2] + (1 - Pr(a_1 < a_2|a_1))E[\theta_1|a_1, a_1 > a_2] = E[\theta_1|a_1] < E[\theta_1|a_1, a_1 > a_2]$. Suppose agent 1 anticipates learning whether $a_1 < a_2$ or $a_1 > a_2$ after he makes his decision. Then he solves: $max_{a_1} Pr(a_1 < a_2|a_1)V\big(E[\theta_1|a_1, a_1 < a_2])\big) + (1 - Pr(a_1 < a_2|a_1))V\big(E[\theta_1|a_1, a_1 > a_2]\big) - C(a_1, \omega_1 - \theta_1)$. If agent 1 knows he will obtain no information about a_2, then he will solve $max_{a_1} V(E[\theta_1|a_1]) - C(a_1, \omega_1 - \theta_1)$. Since we assume that marginal utility is convex, we see in figure 2 that the marginal utility of activity is greater when agent 1 knows that he will learn how his choice compares to the choice of agent 2 than when he is to remain ignorant.



Notes: Here $E^{<}_{\theta_1} = E[\theta_1|a_1, a_1 < a_2]$, $E^{>}_{\theta_1} = E[\theta_1|a_1, a_1 > a_2]$, and $p = Pr(a_1 < a_2|a_1)$.

Figure 2: Social Information Anticipation

3 Experimental Design

We conducted two experiments to directly test the predictions of our theory. The first experiment tests the relevance of self image in social comparisons, and the second experiment tests the relevance of signal extraction. In both experiments participants chose the maximum number of real-effort tasks they were willing to complete in exchange for a donation to charity. All experiment sessions were conducted at the University of California, San Diego Department of Economics. Subjects completed the experiment on individual computer terminals. Privacy screens were installed on each computer and barriers were placed between every subject. All participants were current undergraduates at U.C.S.D. Each subject was paid 15 dollars for their participation, and experiment sessions took approximately 50 minutes. Treatments were varied across sessions for a between-subjects design. Recruitment for each session was done by emailing a random sample of U.C.S.D. undergraduates. The first experiment contained nine to fourteen subjects per session, and the second experiment contained eight to twelve subjects per session.

Section 3.1 explains the real-effort task choice. Section 3.2 details the self-image experiment, and section 3.3 describes the test for signal extraction.

3.1 The Task Choice

In both experiments, participants were asked to select the maximum number of real-effort tasks they were willing to complete in exchange for donations to the Afghan Dental Relief Project. The A.D.R.P. is a charitable organization that provides free dental services and dental health education to the poorest families and individuals in Kabul, Afghanistan. 100% of the donations that were generated from the experiment were used to purchase dental supplies for A.D.R.P.'s free dental clinic. We collaborated with the A.D.R.P. because it is a deserving and relatively unknown charity. The founder, Dr. James Rolfe, agreed to monitor gifts made to the charity during the course of our experiment. Dr. Rolfe reports that no gifts were made to the A.D.R.P. that could have been given by a U.C.S.D. undergraduate.[11]

The real-effort task was to transcribe captchas. Captchas are distorted images of a sequence of letters commonly used by website developers to distinguish between human users and bots. The task was deliberately made to be more frustrating and tedious than typical website captchas.[12] Our captchas consisted of capital and lowercase letters, numbers, and special characters. Only correctly transcribed captchas were considered completed tasks. Subjects were given three chances per randomly assigned captcha and they could not skip an assigned captcha except by deliberately entering three incorrect responses.[13] The typical participant was able to correctly transcribe 1-out-of-every-5 captchas. An example of the task is show in figure 3.[14]

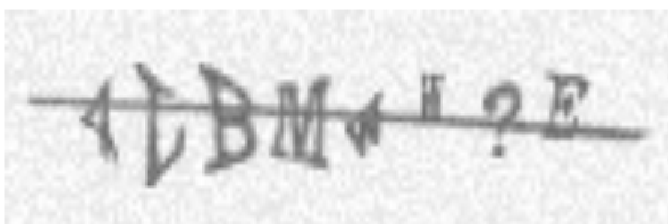


Figure 3: Example Task

In the self-image experiment subjects selected the maximum number of tasks they were willing to complete in exchange for donations of $2, $5, $10, $15, and $20. Each subject chose between 0 and 50 tasks for each possible donation amount. We ensured the incentive compatibility of this decision by randomly assigning each subject a donation and task amount after they had completed making their decisions. Each subject drew a ball out of an jar with a donation amount and corresponding 3-digit code. They then entered their codes into their computer terminals to confirm their assigned donations. A random number generator then assigned each subject a number of tasks (between 0 and 50). Both randomization devices were fair – every donation and task combination had an equal probability of being assigned.

[11]Specifically, all donations made to the A.D.R.P. during the course of our experiment came from us, the experimenters, or from members of Dr. Rolfe's local Santa Barbara community.

[12]Captchas were generated using the Python module `Claptcha`, available here: https://github.com/kuszaj/claptcha. All use of this module is in accordance with the license outlined at the previous link. The font used for captchas was "Mom's Typewriter," an open-source font available here: https://www.dafont.com/moms-typewriter.font.

[13]All captchas were randomly assigned out of a bank of 1000 captcha images.

[14]The correct transcription of the shown captcha is "4LBMwW?E"

If the assigned number of tasks was equal to or fewer than the maximum number they were willing to do for their assigned donation, they completed their assigned number of tasks and we gave the assigned donation to the A.D.R.P. For example, suppose that for a donation of $15 a participant chose to do at most 30 tasks. If he were randomly assigned $15 and 20 tasks, then he completed 20 tasks and $15 was given to the Afghan Dental Relief Project. On the other hand, if he was randomly assigned $15 and 40 tasks, then he did 0 tasks and no donation was given to the A.D.R.P. Subjects were offered the same choice in the signal-extraction experiment. However, only a donation of $20 was possible – therefore subjects in the signal extraction experiment only made one decision.

All experiment treatments followed a similar structure. Subjects were first introduced to the charity by reading a short news article. Second, all subjects attempted five sample captchas so that they were familiar with the task. Third, subjects received instruction and comprehension testing about the incentive compatible task choice. Lastly, subjects made their decisions under the conditions of the treatment they were assigned. In all treatments, subjects were free to leave as soon as they completed their assigned tasks. Importantly, individuals never observed the decisions of others in their own session, nor did they observe the randomly assigned donations or task amounts of other participants in their session.

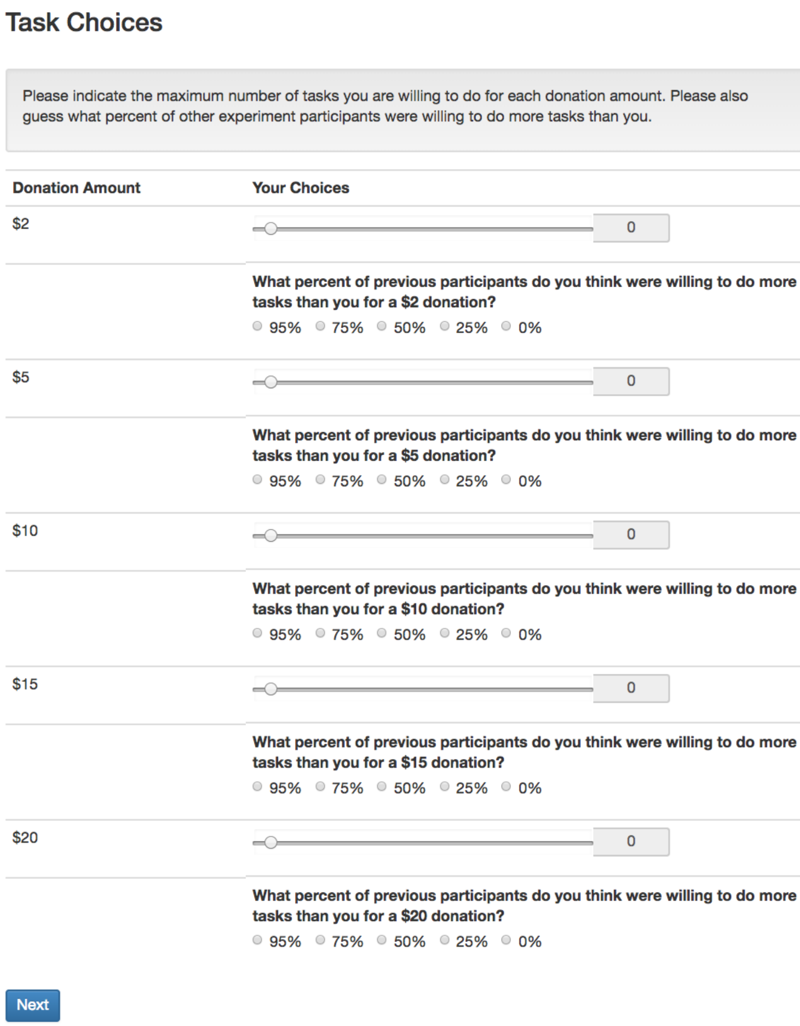
3.2 Self Signalling and Social Comparisons

The first experiment tests our theory's prediction that individuals will choose more costly actions in anticipation of social information. In the context of our experiment this implies that individuals will be willing to complete more captchas when they will learn how their choice compares to the choices of previous participants. We use this prediction to identify the role of self image in social comparisons.

In both treatment and baseline, participants chose the maximum number of captchas they were willing to complete in exchange for donations of $2, $5, $10, $15, and $20 – as described in section 3.1. In conjunction with their choices, subjects were also asked to predict the percent of all previous participants that were willing to complete more tasks than them for each of their decisions. This decision is depicted in figure 4. As figure 4 shows, subjects selected the maximum number of tasks they were willing to complete and guessed whether 95%, 75%, 50%, 25%, or 0% of all previous participants were willing to do more tasks them. For example, suppose that for a donation of $10 dollars an individual chose to do a maximum of 12 tasks. Further suppose that this person thought that at least 50%, but fewer than 75%, of all previous participants were willing to do more than 12 tasks for a $10 donation. This person was then instructed to indicate that he believes that at least 50% of all previous experiment participants were willing to do more tasks than him for a $10 donation.

In treatment sessions, participants were given sealed envelopes that they opened *after* submitting their decisions and distributional guesses. These envelopes contained the true 5th, 25th, 50th, 25th, and 100th percentiles for task choice by donation amount. Treatment participants then submitted the correct answers for what percent of previous participants were willing to do more tasks than them for each possible donation.

All choices were recorded anonymously. No subject choice, assigned donation, or assigned task amount was revealed to others in their sessions. Further, while only treatment subjects ultimately learned the percentiles of previous participant choices, we deliberately asked all



Notes: This is the decision screen for participants in the self-image experiment.

Figure 4: Decision Screen

participants to consider how their choices compare to the choices of all previous participants. By doing so, we made subjects in both baseline and treatment cognizant of what the experimenter observes. That is, we made all experiment subjects aware that the experimenter will observe the full anonymous distribution of participant choices. Since the experimenter's information set is identical in treatment and baseline, any difference in subject behavior is solely due to subjects anticipating what they themselves will learn.[15]

[15]There is an second order equilibrium concern that we must address. Specifically, if all subjects in the baseline thought all previous participants were also in the baseline – and all treatment participants thought all previous participants were in the treatment – then subjects in the treatment may have had higher beliefs about what previous participants chose to do. Similarly, if only treatment subjects were aware that their anonymous choices may be revealed in future sessions, then social image could still be a confounding factor. *However, we preclude these possible concerns by explaining to subjects in both treatment and baseline that 50% of all experiment sessions receive social information and 50% do not.* At no point do we reveal how

3.3 Signal Extraction and Peer-Group Formation

All of the predicted dynamics of our proposed theory rely on signal extraction. Therefore, peer effects are predicted to arise only if group behavior provides a sufficiently refined signal. In the context of our experiment, our theory states that decision makers may refer to others' choices to better understand whether their own choices reveal selfishness or task difficulty. As such, we use statistically garbled and refined social information to directly test the relevance of signal extraction dynamics to our decision environment.

As described in section 3.1, participants in this experiment chose the maximum number of captchas they were willing to complete in exchange for a $20 donation to the A.D.R.P. Prior to their decision, each person was informed that they would receive one of the two following statements on the choices of all previous participants.

1. *More than **50%*** of all previous participants were willing to complete at least 20 tasks for a donation of $20.

2. *Less than **25%*** of all previous participants were willing to complete at least 20 tasks for a donation of $20.

Subjects received their signals by drawing one of sixteen available envelopes at random. 8-out-of-16 envelopes contained the true statement in the baseline, while 15-out-of-16 envelopes contained the true statement in the treatment.[16] Clearly, previous participant choices do not depend on the drawn statement of any current participant. Therefore, all that changes between treatment and baseline is the underlying probability of drawing a true or false signal. After reading their signals and choosing how many tasks they were willing to complete, subjects also indicated which signal they believed to be true.[17]

Signal extraction has a specific hypothesis in this context. Baseline subjects should understand that variation in the obtained signal is pure noise, and their task choices and beliefs should be independent of the obtained signal. Furthermore, if subjects are sensitive to statistically refined peer data, treatment participants who receive the high signal should choose to do more tasks than all baseline participants. If both hypotheses hold true, then treatment participants who receive the high signal should also choose to do more tasks than baseline participants who receive the high signal.

4 Results

Section 4.1 corroborates our theory's prediction that individuals will choose more costly actions to bolster self image in anticipation of social information. Section 4.2 supports the relevance of image signal extraction in our experiment.

many sessions have taken place or how many remain. Therefore, all subjects were uniformly in the dark about the probability that their choices will inform future revelations of social information.

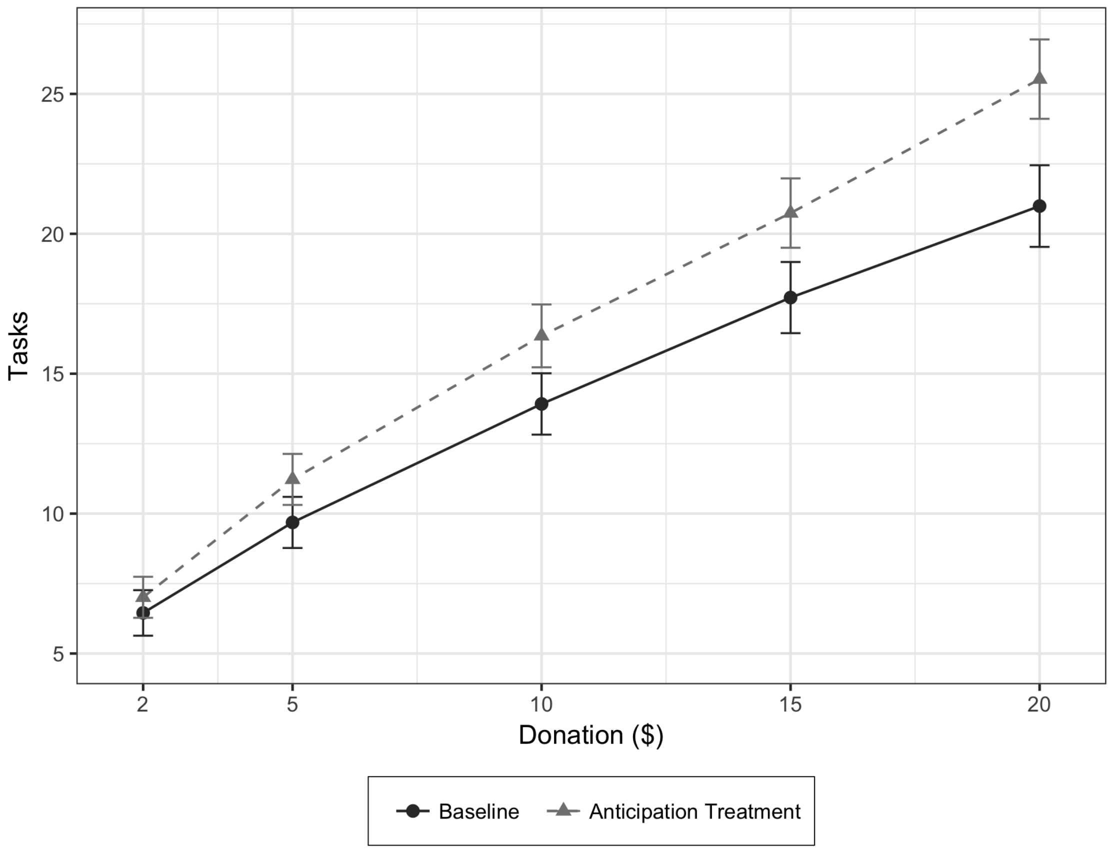
[16] The high signal – signal 1 – is the true signal.

[17] Subjects were not informed that they would be asked which signal they believed until after they made their decisions.

4.1 Self-Image Results

Figure 5 plots the average task choice by donation amount of those in the baseline and anticipation treatments. Those in the anticipation treatment were, on average, willing to complete more captchas than those in the baseline. We also observe that task choice is increasing in the donation amount,[18] and that the treatment effect increases in the donation amount.

Figure 5: Mean Task Choice by Donation



Notes: This figure plots the average number of tasks subjects were willing to complete for each possible donation. In concordance with self signaling, subjects choose to do more tasks if they anticipate learning how their choices compare to the choices of previous participants. This effect is increasing in the value of the gift to charity. Standard errors are shown in brackets.

Table 1 presents these results via estimation of the following regressions:

$$y_{i,d} = \alpha_0 + \alpha_1 Donation_{i,d} + \alpha_2 Treat_i + \varepsilon_{i,d} \tag{7}$$

$$y_{i,d} = \beta_0 + \beta_1 Donation_{i,d} + \beta_2 Treat_i + \beta_3 Treat_i \times Donation_{i,d} + \varepsilon_{i,d} \tag{8}$$

where $y_{i,d}$ is the maximum number of tasks subject i was willing to complete for donation

[18] 94% of all participants displayed within-subject monotonicity in task choice across the donation amounts.

Table 1: Effect of Treatment on Tasks Allocation

	DV: Task Choice	
	(1)	(2)
Donation	0.903***	0.802***
	(0.045)	(0.064)
Treatment	2.417*	0.296
	(1.452)	(1.152)
Treat × Donation		0.204**
		(0.089)
Constant	4.367***	5.413***
	(0.928)	(0.817)
R-Squared	0.208	0.211
Subjects	219	219
Observations	1095	1095

Notes: This table quantifies the results shown in figure 5. Robust standard errors, clustered at the subject level, are presented in parentheses. There are 108 participants in the treatment and 111 in the baseline.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

d. Regression 8 is more informative.[19] From this regression we can see that for every additional $5 donated to the A.D.R.P., baseline participants were willing to do an additional four tasks while treatment participants were willing to do an additional five tasks. This result, significant, at the 5% level, is useful for two principle reasons. First, strict monotonicity in task performance over donation size demonstrates the costliness of captcha transcription. Secondly, we find no evidence of any fixed treatment effect – the estimation of β_2 is indistinguishable from 0. Rather, the anticipatory image effect is entirely tied to the size of the gift given to the A.D.R.P. This result is accommodated by our model. A nominal gift of $2 gives little reason to hedge against bad news by making more costly choices. However, subjects choose to do 20% more tasks when the gift is $15 or $20. In other words, anticipatory image concerns only exist when sufficient charitable stakes are attached to an otherwise vacuous task.[20]

[19] Table A1 confirms that the linearly interacted regression is the correct specification. The corresponding regression for table A1 is $y_{i,d} = \delta_0 + \sum_{d\in\{2,5,10,15,20\}} \delta_{1,d} 1_{i,donation=d} + \sum_{d\in\{2,5,10,15,20\}} \delta_{2,d} Treat_i \times 1_{i,donation=d} + \varepsilon_{i,d}$. From this regression we can not only see that task choices and the treatment effect are increasing in the donation, but also that a linear approximation of these effects fits well. For example, regression 8 predicts that the total average treatment effect for donations of $15 and $20 will be 3 and 4 tasks while the indicator regression finds the effects to be 3 and 4.5 tasks.

[20] This finding also further corroborates our interpretation that the treatment effect is driven by self-image concerns. While no subjects learn the decisions, donation assignments or task allocations of others in their session, it is plausible that earlier experiment departures were taken as a signal of lower task choice. Of course, this feature is consistent across both treatments. Therefore, social image concerns could only enhance our treatment effect if subjects thought that learning the true distribution of previous choices would induce

4.2 Signal Extraction Results

In accordance with our theory, we find that participants' choices are highly sensitive to the receipt of a statistically refined signal and unresponsive to a fully garbled signal. Recall that our theory requires that baseline choices should be independent of the obtained signal. Furthermore, treatment participants who receive the high signal should also choose to do more tasks than baseline participants who receive either signal. Figure 6 shows that baseline participant choices differ by a statistically insignificant two tasks between low and high signals. However, subjects who received the true signal with 15-out-of-16 probability chose, on average, 5.5 more tasks than those who received the high signal in baseline, and an average of 5.8 more tasks than all subjects in the baseline. These results are quantified in table 2.

Additionally, we find that 53% of individuals believe signals received in baseline, while 87% of individuals believe signals received in treatment.[21] Notably, individual beliefs are highly predictive of task choice. We find that those who believe the high signal is true are willing to do an average of 12 more tasks than those who believe the low signal. As table A2 shows, this result holds true controlling for signal and treatment.

Lastly, we examine the distributional shift in task choice from baseline to treatment. Assuming monotonicity, figure A1 shows that the treatment effect is delivered by those who would have otherwise chosen to do fewer than 20 tasks in the baseline. This is reflected in tables A3 and A4. Table A3 demonstrates that 73% of treatment participants choose to do at least 20 tasks while only 52% of baseline participants choose to do 20 or more tasks. Further, quantile regression results in tables A4 and A5 show that those below the median chose do to significantly more tasks in response to the treatment, while those above the median do not. Through the lens of our theory, these results, in conjunction with the results shown in table A2, suggest that those who choose to do fewer than 20 tasks in the baseline do so under the belief that most others made the same decision. However, in the treatment, the refined signal corrects their beliefs and they choose to complete more captchas.[22]

Our theory relies on signal extraction as the mechanism underlying behavioral changes following the receipt of social information. Thus, establishing that signal extraction occurs in practice is vital to demonstrating the viability of our theory as predictive of behavior resulting from social interactions. Not only should the receipt of more reliable social information alter behavior, but it should alter individuals' underlying beliefs which induce this change in behavior. The results outlined above show that the receipt of a refined signal affects both beliefs and actions. Further, our results suggest that those individuals whose beliefs change are those that drive changes in average behavior across treatments.

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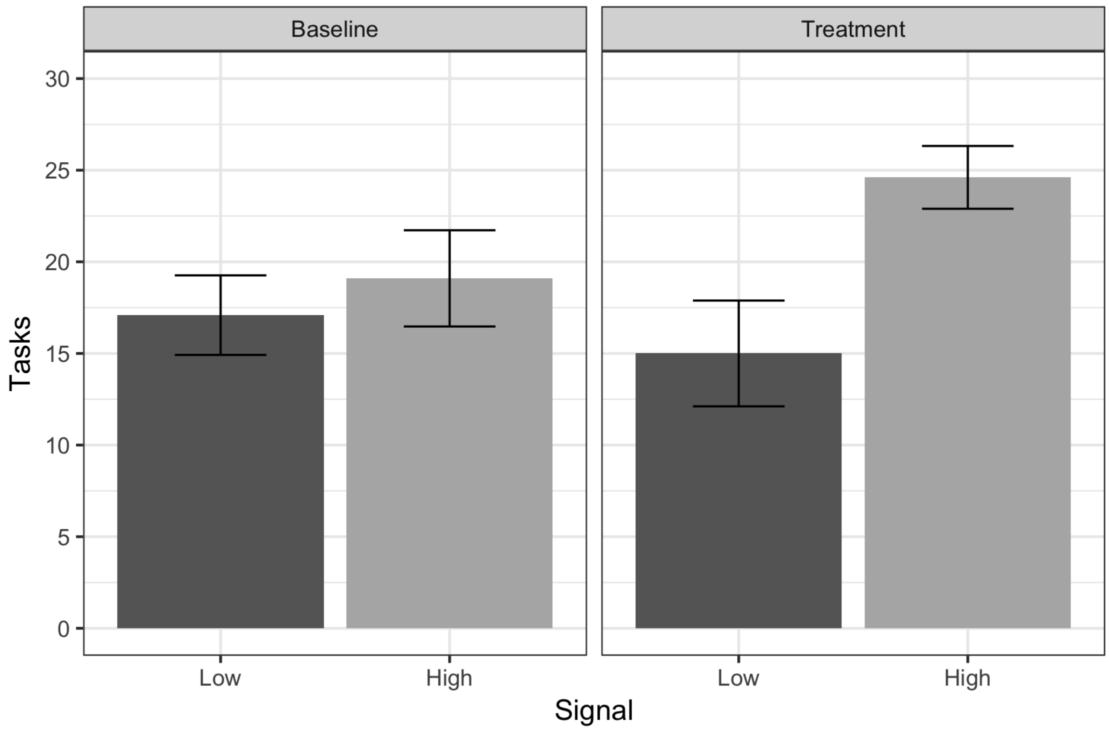
harsher judgment of early departure. However, because no one learned the donation assignment of others, such a hypothesis would be more consistent with the existence of a fixed treatment effect across all possible donations.

[21] This difference is significant at the 1% level. See appendix table A7. Beliefs by signal and treatment are shown in figure 7.

[22] A plausible alternative story is that moral wiggle room/wishful thinking leads those who would like to do fewer tasks to believe that everyone else also did few tasks. However, this story cannot explain why a more refined signal would correct deliberately chosen beliefs. Such a story would also have to incorporate the dynamics of signal extraction wherein wishful think is easier to abide by when the received social information is less informative.

Figure 6: Average Tasks Choice by Signal, Treatment



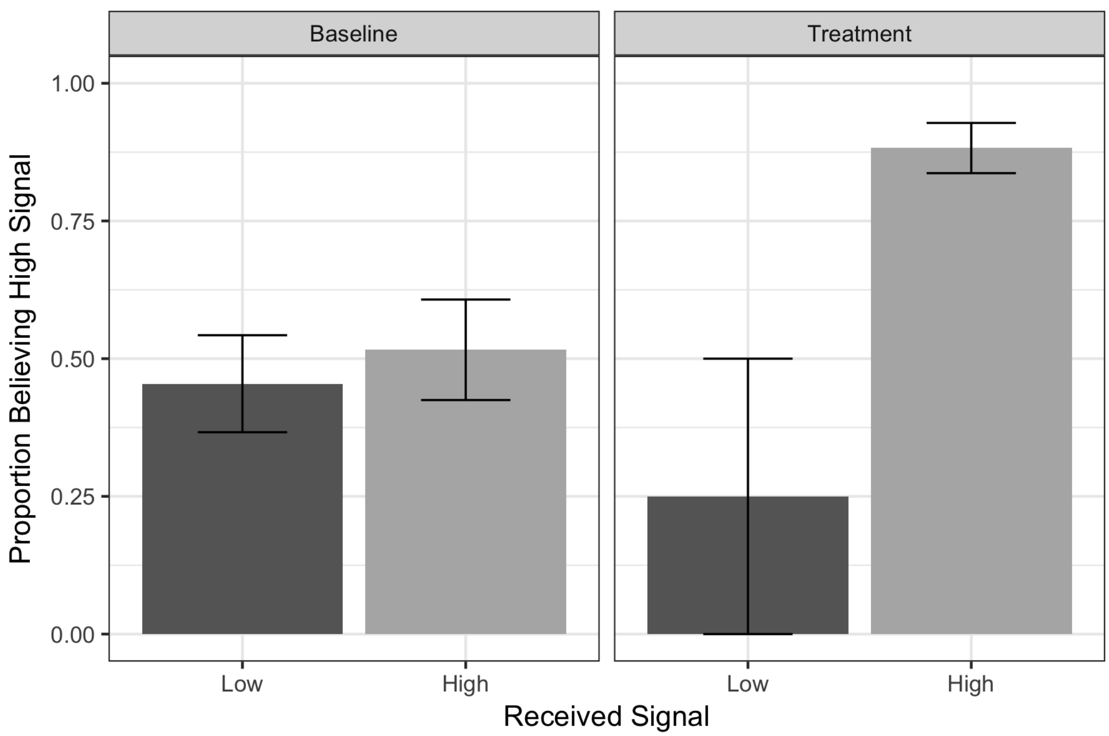
Notes: This figure plots the average number of tasks subjects were willing to complete in exchange for a $20 donation by treatment and signal. The high signal stated that more than 50% of previous participants were willing to complete at least 20 tasks while the low signal stated less than 25% were willing to complete 20 tasks. In concordance with image signal extraction, subjects chose do significantly more tasks when they receive the high signal in treatment – where there is a 15-out-of-16 chance of receiving the true signal – than in the baseline – where there is an 8-out-of-16 chance of receiving the true signal. Brackets represent standard errors.

Table 2: Task Choice by Received Signal

	DV: Task Choice	
	(1)	(2)
	Both Signals	High Signal
Treatment	5.847**	5.511*
	(2.347)	(3.129)
Constant	18.062***	19.097***
	(1.686)	(2.616)
R-Squared	0.050	0.040
Observations	119	82

Notes: Column 1 regresses task choice on treatment for all those in the experiment. Column 2 restricts the same regression to only those who received the high signal. Robust standard errors presented in parentheses.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Figure 7: Distribution of Beliefs by Signal, Treatment



Notes: This figure plots the proportion of subjects who believed that more than 50% of previous participants were willing to complete at least 20 tasks by treatment and signal. In concordance with image signal extraction, participant beliefs are highly dependent on their signals in treatment, where there was a 15-out-of-16 chance of observing the true signal, and unresponsive in baseline where there was a 8-out-of-16 chance of observing the true signal. Brackets represent standard errors.

5 Conclusion

The economic importance of social interactions is well documented. However, there remain open questions at the core of understanding social pressure (Bursztyn and Jensen, 2017). This project complements existing theories of social conformity by theoretically and experimentally examining a justification for peer effects absent norms or stigmas. To that end, we demonstrate that if individuals rely on their own choices as well as social comparisons to form their self image, they will often mimic the behavior of their peers. With no norm to follow, (partial) social conformity arises if decision makers are more afraid of learning that they are of low social type than they are eager to prove that they are of high social type.

We are able to empirically distinguish our rationalization of peer effects from others through novel predictions on peer selection and on the anticipation of social information. In our model, an individual distinguishes between peer behavior that is or is not relevant to his own decision making by how informative other's choices are to his self image. This theory predicts the signal that peer choice provides is refined in the similarity of incentives and costs faced by decision makers. Further, our theory predicts that individuals will make more costly and image-positive choices in anticipation of social information. We test these predictions in a series of lab experiments. In accordance with our theory, experiment participants choose costlier actions in anticipation of social information, and their choices adhere to basic signal extraction dynamics.

Our results establish a foundation for further exploration of the role of self and social signaling in peer effects. Specifically, our theory predicts that differences in extrinsic incentives and costs will act as signal interference and diminish the impact of social comparisons, thereby reducing observed peer effects and social conformity. However, our theory remains largely agnostic as to the scope of peer differences and environmental considerations that may be interpreted as signal interference. For example, while our theory clearly predicts that an individual who performs a task for charity will react less to decisions made by someone who is paid a wage for the task, it may also explain why a graduate student feels more compelled to donate to the Salvation Army when observing others do so at Aldi than at Whole Foods. That is, differential peer effects between individuals with differentiated observable personal traits is potentially explained by perceived signal interference.

A potentially relevant literature documents an important relationship between uncertainty and self-serving preferences (Dana et al., 2007; Andreoni and Bernheim, 2009; Exley, 2016). Excuse driven preferences may exacerbate the effect of perceived signal interference in image signaling. Therefore, exploring this relationship may provide better predictive power over the environmental conditions and policy interventions that will catalyze or mitigate social conformity. Lastly, our theory can be naturally extended to yield predictions on when individuals will seek or avoid information. Such predictions could potentially be used to understand when social information is deemed harmful, beneficial, or irrelevant to one's own image. Such a research agenda has potentially broad implications for work-place, school, and social practices, and may provide greater predictive power on how to shape peer influence across diverse social contexts.

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A Appendix

A.1 Results Appendix

Table A1: Effect of Treatment on Tasks Allocation, by Donation

	DV: Tasks Choice
\$5	3.234***
	(0.472)
\$10	7.468***
	(0.741)
\$15	11.270***
	(0.957)
\$20	14.541***
	(1.185)
Treat x \$2	0.559
	(1.098)
Treat x \$5	1.538
	(1.293)
Treat x \$10	2.433
	(1.572)
Treat x \$15	3.020*
	(1.779)
Treat x \$20	4.537**
	(2.038)
Constant	6.450***
	(0.815)
R-Squared	0.212
Subjects	219
Observations	1095

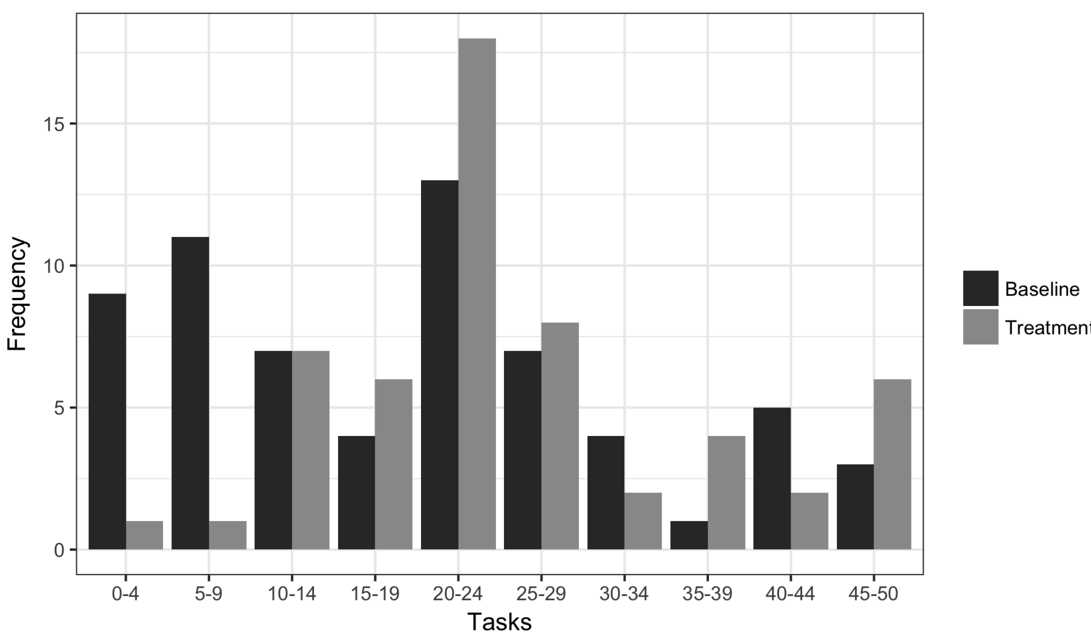
Notes: This table individually presents the results of figure 5 for each donation amount. Robust standard errors, clustered at the subject level, presented in parentheses.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table A2: Task Choice by Belief, Signal, Treatment

	DV: Task Choice	
	(1)	(2)
High Belief	12.736***	11.931***
	(2.151)	(2.599)
High Signal		1.420
		(2.504)
Treatment		1.018
		(2.642)
Constant	12.524***	11.596***
	(1.638)	(1.673)
R-Squared	0.216	0.221
Observations	119	119

Notes: We regress task choice on an indicator that the subject believes the high signal is true. Robust standard errors presented in parentheses.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Figure A1: Distribution of Task Choice by Treatment



Notes: This figure shows that the difference in task choice between treatment and baseline arises from subjects who were willing to do 20 or fewer tasks. Given the established correlation between choice and beliefs, this figure suggests that the refined signal corrected beliefs so that more subjects believed the high signal and, consequently, were wiling to do more tasks.

Table A3: Effect of Treatment on Likelihood of Choosing At Least Twenty Tasks

	DV: 1{Tasks $\geq$ 20}
Treatment	0.212**
	(0.087)
Constant	0.516***
	(0.063)
R-Squared	0.047
Observations	119

Notes:We regress an indicator for choosing to do 20 or more tasks on treatment. Robust standard errors in parantheses.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table A4: Quantile Regressions

	DV: Task Choice				
	(1)	(2)	(3)	(4)	(5)
Quantiles	20th	40th	50th	60th	80th
Treatment	10.000***	10.000***	0.000	3.000	5.000
	(2.434)	(3.099)	(3.045)	(3.068)	(6.612)
Constant	5.000***	10.000***	20.000***	20.000***	30.000***
	(1.864)	(2.438)	(2.365)	(2.502)	(3.523)
R-Squared	0.050	0.050	.	0.050	0.050
Observations	119	119	119	119	119

Notes: This table quantifies the distributional difference in task choice shown in figure A1. Standard errors in parantheses.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table A5: Quantile Regressions

	DV: Task Choice				
	(1)	(2)	(3)	(4)	(5)
Quantiles	10th	30th	50th	70th	90th
Treatment	8.000**	12.000***	0.000	0.000	5.000
	(3.761)	(2.967)	(3.045)	(3.376)	(6.777)
Constant	2.000	8.000***	20.000***	25.000***	40.000***
	(1.981)	(2.046)	(2.365)	(2.621)	(5.485)
R-Squared	0.050	0.050	.	.	0.050
Observations	119	119	119	119	119

Notes: Standard errors in parantheses.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table A6: Small Sample t-test: Effect of High Signal on Task Choice

	Task Difference
High Signal	9.608**
	(3.357)
N High Signal	51
N Low Signal	4
N Overall	55

Notes: Standard errors in parantheses.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table A7: Effect of Treatment on Belief of Received Signal

	DV: 1{Believe Signal}
Treatment	0.341***
	(0.078)
Constant	0.531***
	(0.063)
R-Squared	0.135
Observations	119

Notes: Standard errors in parantheses.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

A.2 Theoretical Appendix

A.2.1 Proposition 1

Define $a_1^* = \text{argmax}_{a_1} U(a_1, a_2, \ldots, a_N) - C(a_1, \omega_1 - \theta_1)$. Then, for all $i \in \{2, \ldots, N\}$

$$\frac{\partial a_1^*}{\partial a_i} = \frac{-V''\left(E[\theta_1|a_1,a_i]\right)\frac{\partial E[\theta_1|a_1,a_i]}{\partial a_i}}{V''\left(E[\theta_1|a_1,a_i]\right)\frac{\partial E[\theta_1|a_1,a_i]}{\partial a_1} - \frac{\partial^2 C}{\partial a_1^2}(a_1, \omega_1 - \theta_1)}$$

Proof.

$$max_{a_1} U(a_2) - C(a_2, \omega_2 - \theta_2)$$

$$\vdots$$

$$max_{a_N} U(a_N) - C(a_N, \omega_N - \theta_N)$$

$$max_{a_1} U(a_1, a_2, \ldots, a_N) - C(a_1, \omega_1 - \theta_1)$$

This results in the first order conditions:

$$\frac{\partial U}{\partial a_2}(a_2) - \frac{\partial C}{\partial a_2}(a_1, \omega_1 - \theta_1) = 0$$

$$\vdots$$

$$\frac{\partial U}{\partial a_N}(a_N) - \frac{\partial C}{\partial a_N}(a_N, \omega_N - \theta_N) = 0$$

$$\frac{\partial U}{\partial a_1}(a_1, a_2, \ldots, a_N) - \frac{\partial C}{\partial a_1}(a_1, \omega_1 - \theta_1) = 0$$

Rewrite these equations as $F_1(X,Y) = 0, \ldots, F_N(X,Y) = 0, F_s(X,Y) = 0$ where $X = (a_1, \ldots, a_s)$ and $Y = (\theta_1, \omega_1, \ldots, \theta_s, \omega_s)$. Further define $F(X,Y) = (F_1, \ldots, F_s)$ and define $G(Y)$ such that $F(G(Y), Y) = (0, \ldots, 0)$ for all Y. Again define $A_x = F_X(X,Y)$ and $A_y = F_Y(X,Y)$.

$$A_x = \begin{bmatrix} \frac{\partial F_1}{\partial a_1} & \frac{\partial F_1}{\partial a_2} & \ldots & \frac{\partial F_1}{\partial a_N} \\ 0 & \frac{\partial F_2}{\partial a_2} & \ldots & 0 \\ \vdots & \vdots & & \vdots \\ 0 & 0 & \ldots & \frac{\partial F_N}{\partial a_N} \end{bmatrix} \quad A_y = \begin{bmatrix} \frac{\partial F_1}{\partial \theta_1} & \frac{\partial F_1}{\partial \omega_1} & 0 & 0 & \ldots & 0 & 0 \\ 0 & 0 & \frac{\partial F_2}{\partial \theta_2} & \frac{\partial F_2}{\partial \omega_2} & \ldots & 0 & 0 \\ \vdots & \vdots & & & & \vdots & \vdots \\ 0 & 0 & 0 & 0 & \ldots & \frac{\partial F_N}{\partial \theta_N} & \frac{\partial F_N}{\partial \omega_N} \end{bmatrix}$$

Now

$$A_x^{-1} = \begin{bmatrix} \left(\frac{\partial F_1}{\partial a_1}\right)^{-1} & -\frac{\partial F_1}{\partial a_2}\left(\frac{\partial F_2}{\partial a_2}\frac{\partial F_1}{\partial a_1}\right)^{-1} & \dots & -\frac{\partial F_s}{\partial a_N}\left(\frac{\partial F_N}{\partial a_N}\frac{\partial F_s}{\partial a_s}\right)^{-1} \\ 0 & \left(\frac{\partial F_2}{\partial a_2}\right)^{-1} & \dots & 0 \\ \vdots & \vdots & & \vdots \\ 0 & 0 & \dots & \left(\frac{\partial F_N}{\partial a_N}\right)^{-1} \end{bmatrix}$$

$$G'(Y) = -A_x^{-1}A_y =$$

$$\begin{bmatrix} \left(\frac{\partial F_1}{\partial a_1}\right)^{-1}\frac{\partial^2 C}{\partial a_1\partial\theta_1} & \left(\frac{\partial F_1}{\partial a_1}\right)^{-1}\frac{\partial^2 C}{\partial a_1\partial\omega_1} & \frac{-\frac{\partial F_1}{\partial a_2}\frac{\partial^2 C}{\partial a_2\partial\theta_2}}{\frac{\partial F_2}{\partial a_2}\frac{\partial F_1}{\partial a_1}} & \frac{-\frac{\partial F_1}{\partial a_2}\frac{\partial^2 C}{\partial a_2\partial\omega_2}}{\frac{\partial F_2}{\partial a_2}\frac{\partial F_1}{\partial a_1}} & \dots & \frac{-\frac{\partial F_1}{\partial a_N}\frac{\partial^2 C}{\partial a_N\partial\theta_N}}{\frac{\partial F_N}{\partial a_N}\frac{\partial F_1}{\partial a_1}} & \frac{-\frac{\partial F_1}{\partial a_N}\frac{\partial^2 C}{\partial a_N\partial\omega_N}}{\frac{\partial F_N}{\partial a_N}\frac{\partial F_1}{\partial a_1}} \\ 0 & 0 & \frac{\frac{\partial^2 C}{\partial a_2\partial\theta_2}}{\frac{\partial F_2}{\partial a_2}} & \frac{\frac{\partial^2 C}{\partial a_2\partial\omega_2}}{\frac{\partial F_2}{\partial a_2}} & \dots & 0 & 0 \\ \vdots & \vdots & \vdots & \vdots & & \vdots & \vdots \\ 0 & 0 & 0 & 0 & \dots & \frac{\frac{\partial^2 C}{\partial a_N\partial\theta_N}}{\frac{\partial F_N}{\partial a_N}} & \frac{\frac{\partial^2 C}{\partial a_N\partial\omega_N}}{\frac{\partial F_N}{\partial a_N}} \end{bmatrix}$$

Therefore,

$$\frac{\partial a_1^*}{\partial a_i} = \frac{-V''\left(E[\theta_1|a_i,a_1]\right)\frac{\partial E[\theta_1|a_i,a_1]}{\partial a_i}}{\left(V''\left(E[\theta_i|a_i]\right)\frac{\partial E[\theta_i|a_i]}{\partial a_i} - \frac{\partial^2 C}{\partial a_i^2}\right) * \left(V''\left(E[\theta_1|a_i,a_1]\right)\frac{\partial E[\theta_1|a_i,a_1]}{\partial a_1} - \frac{\partial^2 C}{\partial a_1^2}\right)}\left(\frac{\partial^2 C}{\partial a_i\partial\theta_i} + \frac{\partial^2 C}{\partial a_i\partial\omega_i}\right)$$
$$* \left(\frac{1}{V''\left(E[\theta_i|a_i]\right)\frac{\partial E[\theta_i|a_i]}{\partial a_i} - \frac{\partial^2 C}{\partial a_i^2}(a_i,\omega_i-\theta_i)}\left(\frac{\partial^2 C}{\partial a_i\partial\theta_i} + \frac{\partial^2 C}{\partial a_i\partial\omega_i}\right)\right)^{-1}$$

$$\frac{\partial a_1^*}{\partial a_i} = -\frac{V''\left(E[\theta_1|a_i,a_1]\right)\frac{\partial E[\theta_1|a_i,a_1]}{\partial a_i}\left(V''\left(E[\theta_i|a_i]\right)\frac{\partial E[\theta_i|a_i]}{\partial a_i} - \frac{\partial^2 C}{\partial a_i^2}(a_i,\omega_i-\theta_i)\right)}{\left(V''\left(E[\theta_i|a_i]\right)\frac{\partial E[\theta_i|a_i]}{\partial a_i} - \frac{\partial^2 C}{\partial a_i^2}\right) * \left(V''\left(E[\theta_1|a_i,a_1]\right)\frac{\partial E[\theta_1|a_i,a_1]}{\partial a_1} - \frac{\partial^2 C}{\partial a_1^2}\right)}$$

Which yields

$$\frac{\partial a_1}{\partial a_i} = \frac{-V''\left(E[\theta_1|a_1,a_i]\right)\frac{\partial E[\theta_1|a_1,a_i]}{\partial a_i}}{V''\left(E[\theta_1|a_i,a_1]\right)\frac{\partial E[\theta_1|a_i,a_1]}{\partial a_1} - \frac{\partial^2 C}{\partial a_1^2}(a_1,\omega_1-\theta_1)}$$

□

A.2.2 Group Formation Corollaries

We now prove corollaries 1 and 2.

Proof. Recall that

$$\frac{\partial a_1^*}{\partial a_i} = \frac{-V''\left(E[\theta_1|a_1,a_i]\right)\frac{\partial E[\theta_1|a_1,a_i]}{\partial a_i}}{V''\left(E[\theta_1|a_1,a_i]\right)\frac{\partial E[\theta_1|a_1,a_i]}{\partial a_1} - \frac{\partial^2 C}{\partial a_1^2}(a_1,\omega_1-\theta_1)}$$

Therefore, it is sufficient to show that $\frac{\partial E[\theta_1|a_1,a_2]}{\partial a_2}$ is increasing in $cov(\omega_1,\omega_2)$ for any given (a_1,a_2) and that $\frac{\partial E[\theta_1|a_1,a_2]}{\partial a_2} > \frac{\partial E[\theta_1|a_1,a_3]}{\partial a_3}$ if and only if $cov(\omega_1,\omega_2) > cov(\omega_1,\omega_3)$.

Recall that agent i solves $\frac{\partial U}{\partial a_i}(a_i) = \frac{\partial C}{\partial a_i}(a_i,\omega_i-\theta_i)$ where U is a known function. Since C is assumed invertible, given (a_1,a_i), agent 1 knows $\omega_1-\theta_1$ and $\omega_i-\theta_i$. Therefore, $E[\theta_1|a_1,a_i] = E[\theta_1|\omega_1-\theta_1,\omega_i-\theta_i]$.

Now let $K_i = \omega_i - \theta_i$. We first establish that K is decreasing in a. Note that $\frac{\partial a^*}{\partial \theta} = \left(V''\left(E[\theta|a]\right)\frac{\partial E[\theta|a]}{\partial a} - \frac{\partial^2 C}{\partial a^2}(a,\omega-\theta)\right)^{-1}\frac{\partial^2 C}{\partial a\partial\theta}(a,\omega-\theta)$ and $\frac{\partial a^*}{\partial \omega} = \left(V''\left(E[\theta|a]\right)\frac{\partial E[\theta|a]}{\partial a} - \frac{\partial^2 C}{\partial a^2}(a,\omega-\theta)\right)^{-1}\frac{\partial^2 C}{\partial a\partial\omega}(a,\omega-\theta)$. But,

$$\begin{aligned}\frac{\partial K}{\partial a} = \frac{\partial}{\partial a}\omega-\theta = \frac{\partial \omega}{\partial a}-\frac{\partial \theta}{\partial a} &= \left(L''\left(E[\theta|a]\right)\frac{\partial E[\theta|a]}{\partial a} - \frac{\partial^2 C}{\partial a^2}(a,\omega-\theta)\right)\frac{\partial^2 C}{\partial a\partial(\omega-\theta)}(a,\omega-\theta)^{-1} \\ &+ \left(L''\left(E[\theta|a]\right)\frac{\partial E[\theta|a]}{\partial a} - \frac{\partial^2 C}{\partial a^2}(a,\omega-\theta)\right)\frac{\partial^2 C}{\partial a\partial(\omega-\theta)}(a,\omega-\theta)^{-1} < 0\end{aligned}$$

By definition we have that $E[\theta_i|a_i,a_j] = E[\theta_i|K(a_i),K(a_j)] = E[\theta_i|K_i,K_j]$. As such,

$$\frac{\partial E[\theta_1|a_1,a_i]}{\partial a_i} = \frac{\partial E[\theta_1|K_1,K_i]}{\partial K_i}\frac{\partial K_i}{\partial a_i}$$

is decreasing – more negative – in $\frac{\partial E[\theta_1|K_1,K_i]}{\partial K_i}$.

Let ω be distributed $N(\omega_0,\sigma_\omega)$ and θ be distributed $N(\theta_0,\sigma_\theta)$. Suppose that we have N observations of $\omega_i-\theta_i$. What is $E[\theta_1|\omega_1-\theta_1,\dots,\omega_N-\theta_N]$?

Consider the following vector of random variables:

$$\boldsymbol{x} = \begin{bmatrix}\theta_1 \\ \omega_1-\theta_1 \\ \vdots \\ \omega_N-\theta_N\end{bmatrix}$$

Because θ_i and ω_i are normally distributed, $\boldsymbol{x} \sim N(\boldsymbol{\mu},\boldsymbol{\Sigma})$. Where:

$$\boldsymbol{\mu} = \begin{bmatrix}E[\theta_1] \\ E[\omega_1-\theta_1] \\ \vdots \\ E[\omega_N-\theta_N]\end{bmatrix}$$

$$\mathbf{\Sigma} = \begin{bmatrix} Var(\theta_1) & Cov(\theta_1, \omega_1 - \theta_1) & \dots & Cov(\theta_1, \omega_N - \theta_N) \\ Cov(\theta_1, \omega_1 - \theta_1) & Var(\omega_1 - \theta_1) & \dots & Cov(\omega_1 - \theta_1, \omega_N - \theta_N) \\ \vdots & \vdots & & \vdots \\ Cov(\theta_1, \omega_N - \theta_N) & Cov(\omega_1 - \theta_1, \omega_N - \theta_N) & \dots & Var(\omega_N - \theta_N) \end{bmatrix}$$

$$= \begin{bmatrix} Var(\theta_1) & -Var(\theta_1) & \dots & 0 \\ -Var(\theta_1) & Var(\omega_1 - \theta_1) & \dots & Cov(\omega_1, \omega_N) \\ \vdots & \vdots & & \vdots \\ 0 & Cov(\omega_1, \omega_N) & \dots & Var(\omega_N - \theta_N) \end{bmatrix}$$

We can partition $\boldsymbol{x}$ into x_1 and $\boldsymbol{x_2}$, where:

$$x_1 = \theta_1$$
$$\boldsymbol{x} = \begin{bmatrix} \omega_1 - \theta_1 \\ \vdots \\ \omega_N - \theta_N \end{bmatrix}$$

Also, we partition the covariance matrix $\mathbf{\Sigma}$ as follows:

$$\mathbf{\Sigma} = \begin{bmatrix} Var(\theta_1) & \mathbf{\Sigma_{12}} \\ \mathbf{\Sigma_{21}} & \mathbf{\Sigma_{22}} \end{bmatrix}$$

where:

$$\mathbf{\Sigma_{12}} = \mathbf{\Sigma_{21}^{\intercal}} = \begin{bmatrix} -Var(\theta_1) & 0 & \dots & 0 \end{bmatrix}$$
$$\mathbf{\Sigma_{22}} = \begin{bmatrix} Var(\omega_1 - \theta_1) & \dots & Cov(\omega_1, \omega_N) \\ \vdots & & \vdots \\ Cov(\omega_1, \omega_N) & \dots & Var(\omega_N - \theta_N) \end{bmatrix}$$

Then, we can use the following identity for multivariate normal distributions to find the expected value of x_1 conditional on $\boldsymbol{x} = \boldsymbol{a}$:

$$E[x_1 | \boldsymbol{x_2} = \boldsymbol{a}] = E[x_1] + \mathbf{\Sigma_{12}} \mathbf{\Sigma_{22}^{-1}} (\boldsymbol{a} - E[\boldsymbol{x}])$$

$$\mathbf{\Sigma_{12}} \mathbf{\Sigma_{22}^{-1}} = \frac{-Var(\theta)}{|\Sigma_{22}|} \times \begin{bmatrix} M_{1,1} & -M_{1,2} & \dots & (-1)^{N+1} M_{1,N} \end{bmatrix}$$

Where $M_{i,j}$ is the determinant of the $(N-1)\times(N-1)$ matrix that results from deleting row i and column j of $\mathbf{\Sigma}_{22}$. Since $\mathbf{\Sigma}_{22}$ is a symmetric matrix we have applied the property that $\mathbf{\Sigma}_{22}^{-1} = \frac{adjoint\, of\, \mathbf{\Sigma}_{22}}{|\mathbf{\Sigma}_{22}|}$.

This implies that the coefficient on the term $[\omega_i - \theta_i - E[\omega - \theta]]$ is $\frac{-Var(\theta)}{|\Sigma_{22}|}(-1)^{i+1}M_{1,i}$. Corollaries 1 and 2 follow directly.

□

A.2.3 Anticipation Effect

We know prove a_1^* increases in anticipation of social information.

Proof. Now the left hand side of 6 is larger than 5 by Jensen's inequality (since $V''' > 0$) if $\frac{\partial E[\theta_s|a_s,n+1]}{\partial a_s} - \frac{\partial E[\theta_s|a_s,n]}{\partial a_s} \leq 0$ (since $V'' < 0$) and $\sum_{n=1}^{N} P_n'(a_s)V\left(E\left[\theta_s|a_s,n\right]\right) > 0$.

We first establish that $\sum_{n=1}^{N} P_n'(a_s)V\left(E\left[\theta_s|a_s,n\right]\right) > 0$. Note that $\sum_{n=1}^{N} P_n'(a_s) = 0$. Therefore we can establish $\sum_{n=1}^{N} P_n'(a_s)V\left(E\left[\theta_s|a_s,n\right]\right) > 0$ by demonstrating that $\frac{\partial}{\partial a_s}\frac{P_{n+1}(a_s)}{P_n(a_s)} > 0$ and $V\left(E\left[\theta_s|a_s,n+1\right]\right) < V\left(E\left[\theta_s|a_s,n\right]\right)$.

$$\frac{P_{n+1}(a_s)}{P_n(a_s)} = \frac{P_{n+1}(K_s(a_s))}{P_n(K_s(a_s))}$$

$$\frac{\partial}{\partial a_s}\frac{P_{n+1}(a_s)}{P_n(a_s)} = \frac{\partial}{\partial K_s}\frac{P_{n+1}(K_s(a_s))}{P_n(K_s(a_s))}\frac{\partial K_s}{\partial a_s}$$

Now,

$$\frac{P_{n+1}(K_s|\omega)}{P_n(K_s|\omega)} = \frac{F_\theta(\omega - K_s)^n(1-F_\theta(\omega-K_s))^{N-n-1}}{F_\theta(\omega - K_s)^{n-1}(1-F_\theta(\omega-K_s))^{N-n}} = \frac{F_\theta(\omega-K_s)}{1-F_\theta(\omega-K_s)}$$

.

And

$$\frac{\partial}{\partial K_s}\frac{P_{n+1}(K_s|\omega)}{P_n(K_s|\omega)} = \frac{-f_\theta(\omega-K_s)}{(1-F_\theta(\omega-K_s)^2} < 0$$

.

But if $\frac{\partial}{\partial K_s}\frac{P_{n+1}(K_s|\omega)}{P_n(K_s|\omega)} < 0$ for all ω then we know that $\frac{\partial}{\partial K_s}\frac{P_{n+1}(K_s)}{P_n(K_s)} < 0$, and $\frac{\partial}{\partial a_s}\frac{P_{n+1}(a_s)}{P_n(a_s)} = \frac{\partial}{\partial K_s}\frac{P_{n+1}(a_s)}{P_n(K_s(a_s))}\frac{\partial K_s}{\partial a_s} > 0$ because $\frac{\partial K_s}{\partial a_s} < 0$.

We next show that $E[\theta_s|a_s,n+1] > E[\theta|a_s,n]$.

$$E[\theta_s|a_s,n] = \theta_s - \omega + \frac{1}{\int_{\mathbb{R}} f_\theta(\omega-K_s)\Pi_{m<n}F_\theta(\omega-K_s)\Pi_{m>n}(1-F_\theta(\omega-K_s))f_\omega(\omega)d\omega} \int_{\mathbb{R}} \omega f_\theta(\omega-K_s,\omega-K_i)\Pi_{m<n}F_\theta(\omega-K_s)\Pi_{m>n}(1-F_\theta(\omega-K_s))f_\omega(\omega)d\omega$$

Then

$$E[\theta_s|a_s, n+1] - E[\theta_s|a_s, n]$$
$$= \frac{1}{\int_{\mathbb{R}} f_\theta(\omega - K_s)\Pi_{m<n+1}F_\theta(\omega - K_s)\Pi_{m>n+1}(1 - F_\theta(\omega - K_s))f_\omega(\omega)d\omega}$$
$$\int_{\mathbb{R}} \omega f_\theta(\omega - K_s, \omega - K_i)\Pi_{m<n+1}F_\theta(\omega - K_s)\Pi_{m>n+1}(1 - F_\theta(\omega - K_s))f_\omega(\omega)d\omega$$
$$- \frac{1}{\int_{\mathbb{R}} f_\theta(\omega - K_s)\Pi_{m<n}F_\theta(\omega - K_s)\Pi_{m>n}(1 - F_\theta(\omega - K_s))f_\omega(\omega)d\omega}$$
$$\int_{\mathbb{R}} \omega f_\theta(\omega - K_s, \omega - K_i)\Pi_{m<n}F_\theta(\omega - K_s)\Pi_{m>n}(1 - F_\theta(\omega - K_s))f_\omega(\omega)d\omega$$

But

$$\frac{1}{\int_{\mathbb{R}} f_\theta(\omega - K_s)\Pi_{m<n+1}F_\theta(\omega - K_s)\Pi_{m>n+1}(1 - F_\theta(\omega - K_s))f_\omega(\omega)d\omega}$$
$$\int_{\mathbb{R}} f_\theta(\omega - K_s, \omega - K_i)\Pi_{m<n+1}F_\theta(\omega - K_s)\Pi_{m>n+1}(1 - F_\theta(\omega - K_s))f_\omega(\omega)d\omega$$
$$= \frac{1}{\int_{\mathbb{R}} f_\theta(\omega - K_s)\Pi_{m<n}F_\theta(\omega - K_s)\Pi_{m>n}(1 - F_\theta(\omega - K_s))f_\omega(\omega)d\omega}$$
$$\int_{\mathbb{R}} f_\theta(\omega - K_s, \omega - K_i)\Pi_{m<n}F_\theta(\omega - K_s)\Pi_{m>n}(1 - F_\theta(\omega - K_s))f_\omega(\omega)d\omega$$

So the sign of $E[\theta_s|K_s, n+1] - E[\theta_s|K_s, n]$ can be judged by which values of ω receive or lose relative probability density.

Abusing notation,

$$Pr[\omega_s|K_s, n+1] - Pr[\omega_s|K_s, n]$$
$$= \frac{f_\theta(\omega - K_s)\Pi_{m<n+1}F_\theta(\omega - K_s)\Pi_{m>n+1}(1 - F_\theta(\omega - K_s))f_\omega(\omega)}{\int_{\mathbb{R}} f_\theta(\omega - K_s)\Pi_{m<n+1}F_\theta(\omega - K_s)\Pi_{m>n+1}(1 - F_\theta(\omega - K_s))f_\omega(\omega)d\omega}$$
$$- \frac{f_\theta(\omega - K_s)\Pi_{m<n}F_\theta(\omega - K_s)\Pi_{m>n}(1 - F_\theta(\omega - K_s))f_\omega(\omega)}{\int_{\mathbb{R}} f_\theta(\omega - K_s)\Pi_{m<n}F_\theta(\omega - K_s)\Pi_{m>n}(1 - F_\theta(\omega - K_s))f_\omega(\omega)d\omega}$$

$$Pr[\omega_s|K_s, n+1] - Pr[\omega_s|K_s, n]$$
$$= \frac{f_\theta(\omega - K_s)F_\theta(\omega - K_s)^n(1 - F_\theta(\omega - K_s))^{N-n-1}f_\omega(\omega)}{\int_{\mathbb{R}} f_\theta(\omega - K_s)F_\theta(\omega - K_s)^n(1 - F_\theta(\omega - K_s))^{N-n-1}f_\omega(\omega)d\omega}$$
$$- \frac{f_\theta(\omega - K_s)F_\theta(\omega - K_s)^{n-1}(1 - F_\theta(\omega - K_s))^{N-n}f_\omega(\omega)}{\int_{\mathbb{R}} f_\theta(\omega - K_s)F_\theta(\omega - K_s)^{n-1}(1 - F_\theta(\omega - K_s))^{N-n}f_\omega(\omega)d\omega}$$

$$
\begin{aligned}
&Pr[\omega_s|K_s,n+1] - Pr[\omega_s|K_s,n] > 0 \\
&\qquad \iff f_\theta(\omega-K_s)F_\theta(\omega-K_s)^n(1-F_\theta(\omega-K_s))^{N-n-1}f_\omega(\omega) \\
&\qquad - \frac{\int_{\mathbb{R}} f_\theta(\omega-K_s)F_\theta(\omega-K_s)^n(1-F_\theta(\omega-K_s))^{N-n-1}f_\omega(\omega)d\omega}{\int_{\mathbb{R}} f_\theta(\omega-K_s)F_\theta(\omega-K_s)^{n-1}(1-F_\theta(\omega-K_s))^{N-n}f_\omega(\omega)d\omega} \\
&\qquad \times f_\theta(\omega-K_s)F_\theta(\omega-K_s)^{n-1}(1-F_\theta(\omega-K_s))^{N-n}f_\omega(\omega) > 0
\end{aligned}
$$

$$
\begin{aligned}
&Pr[\omega_s|K_s,n+1] - Pr[\omega_s|K_s,n] > 0 \\
&\qquad \iff f_\omega(\omega)f_\theta(\omega-K_s) \\
&\Big[F_\theta(\omega-K_s)^n(1-F_\theta(\omega-K_s))^{N-n-1} - C * F_\theta(\omega-K_s)^{n-1}(1-F_\theta(\omega-K_s))^{N-n}\Big] > 0
\end{aligned}
$$

Where $C = \frac{\int_{\mathbb{R}} f_\theta(\omega-K_s)F_\theta(\omega-K_s)^n(1-F_\theta(\omega-K_s))^{N-n-1}f_\omega(\omega)d\omega}{\int_{\mathbb{R}} f_\theta(\omega-K_s)F_\theta(\omega-K_s)^{n-1}(1-F_\theta(\omega-K_s))^{N-n}f_\omega(\omega)d\omega}$

$$
\begin{aligned}
&Pr[\omega_s|K_s,n+1] - Pr[\omega_s|K_s,n] > 0 \\
&\qquad \iff f_\omega(\omega)f_\theta(\omega-K_s) \\
&\Big[F_\theta(\omega-K_s)^{n-1}(1-F_\theta(\omega-K_s))^{N-n-1}(F_\theta(\omega-K_s) - C + CF_\theta(\omega-K_s))\Big] > 0
\end{aligned}
$$

$$
\begin{aligned}
&Pr[\omega_s|K_s,n+1] - Pr[\omega_s|K_s,n] > 0 \\
&\qquad \iff f_\omega(\omega)f_\theta(\omega-K_s) \\
&\Big[F_\theta(\omega-K_s)^{n-1}(1-F_\theta(\omega-K_s))^{N-n-1}((1+C)F_\theta(\omega-K_s) - C)\Big] > 0
\end{aligned}
$$

Therefore, iff $\omega > F_\theta^{-1}(\frac{C}{1-C}) + K_s$ it receives greater probability weight under rank $n+1$ than under rank n. The opposite is true for $\omega < F_\theta^{-1}(\frac{C}{1-C} + K_s$. Therefore, $E[\theta_s|K_s(a_s), n+1] > E[\theta_s|K_s(a_s), n]$.

Lastly, we will demonstrate $\frac{\partial E[\theta_s|a_s,n+1]}{\partial a_s} - \frac{\partial E[\theta_s|a_s,n]}{\partial a_s} \leq 0$. **Note:** Through all of this we are assuming $K_s(a_s)$ is not rank dependent because a_s is chosen prior to the rank being revealed. Further, K_s is observable to the decision maker at the moment he is making his decision through the marginal cost of his action.

$$\frac{\partial E[\theta_s|K_s,n]}{\partial K_s} = 1 + \frac{\partial}{\partial K_s}\frac{\int_{\mathbb{R}} \omega f_\theta(\omega-K_s)F_\theta(\omega-K_s)^{n-1}(1-F_\theta(\omega-K_s))^{N-n}f_\omega(\omega)d\omega}{\int_{\mathbb{R}} f_\theta(\omega-K_s)F_\theta(\omega-K_s)^{n-1}(1-F_\theta(\omega-K_s))^{N-n}f_\omega(\omega)d\omega}$$

$$\frac{\partial E[\theta_s|K_s,n+1]}{\partial K_s} = 1 + \frac{\partial}{\partial K_s}\frac{\int_{\mathbb{R}} \omega f_\theta(\omega-K_s)F_\theta(\omega-K_s)^{n}(1-F_\theta(\omega-K_s))^{N-n-1}f_\omega(\omega)d\omega}{\int_{\mathbb{R}} f_\theta(\omega-K_s)F_\theta(\omega-K_s)^{n}(1-F_\theta(\omega-K_s))^{N-n-1}f_\omega(\omega)d\omega}$$

$$\begin{aligned}
&\frac{\partial E[\theta_s|K_s,n+1]}{\partial K_s} - \frac{\partial E[\theta_s|K_s,n]}{\partial K_s} \\
&\quad= \frac{\partial}{\partial K_s}\frac{\int_{\mathbb{R}} \omega f_\theta(\omega-K_s)F_\theta(\omega-K_s)^{n}(1-F_\theta(\omega-K_s))^{N-n-1}f_\omega(\omega)d\omega}{\int_{\mathbb{R}} f_\theta(\omega-K_s)F_\theta(\omega-K_s)^{n}(1-F_\theta(\omega-K_s))^{N-n-1}f_\omega(\omega)d\omega} \\
&\quad- \frac{\partial}{\partial K_s}\frac{\int_{\mathbb{R}} \omega f_\theta(\omega-K_s)F_\theta(\omega-K_s)^{n-1}(1-F_\theta(\omega-K_s))^{N-n}f_\omega(\omega)d\omega}{\int_{\mathbb{R}} f_\theta(\omega_i-K_s)f_\theta(\omega-K_s)F_\theta(\omega-K_s)^{n-1}(1-F_\theta(\omega-K_s))^{N-n}f_\omega(\omega)d\omega}
\end{aligned}$$

But

$$\begin{aligned}
&\frac{\partial}{\partial K_s}\frac{\int_{\mathbb{R}} f_\theta(\omega-K_s)F_\theta(\omega-K_s)^{n}(1-F_\theta(\omega-K_s))^{N-n-1}f_\omega(\omega)d\omega}{\int_{\mathbb{R}} f_\theta(\omega-K_s)F_\theta(\omega-K_s)^{n}(1-F_\theta(\omega-K_s))^{N-n-1}f_\omega(\omega)d\omega} \\
&\quad= \frac{\partial}{\partial K_s}\frac{\int_{\mathbb{R}} f_\theta(\omega-K_s)F_\theta(\omega-K_s)^{n-1}(1-F_\theta(\omega-K_s))^{N-n}f_\omega(\omega)d\omega}{\int_{\mathbb{R}} f_\theta(\omega_i-K_s)f_\theta(\omega-K_s)F_\theta(\omega-K_s)^{n-1}(1-F_\theta(\omega-K_s))^{N-n}f_\omega(\omega)d\omega}
\end{aligned}$$

So we consider probability weight given an ω:

$$
\begin{aligned}
&\frac{\partial}{\partial K_s}\frac{f_\theta(\omega-K_s)F_\theta(\omega-K_s)^n(1-F_\theta(\omega-K_s))^{N-n-1}f_\omega(\omega)d\omega}{\int_{\mathbb{R}} f_\theta(\omega-K_s)F_\theta(\omega-K_s)^n(1-F_\theta(\omega-K_s))^{N-n-1}f_\omega(\omega)d\omega}\\
&\qquad=\frac{-1}{\left(\int_{\mathbb{R}} f_\theta(\omega-K_s)F_\theta(\omega-K_s)^n(1-F_\theta(\omega-K_s))^{N-n-1}f_\omega(\omega)d\omega\right)^2}\\
&\qquad\Bigg(\Bigg[F_\theta(\omega-K_s)^n(1-F_\theta(\omega-K_s))^{N-n-1}\left[f'_\theta(\omega_i-K_s)f_\theta(\omega-K_s)f_\omega(\omega)\right]\\
&\qquad+nF_\theta(\omega-K_s)^{n-1}(1-F_\theta(\omega-K_s))^{N-n-1}\left[f_\theta(\omega-K_s)^2f_\omega(\omega)\right]\\
&\qquad-(N-n-1)F_\theta(\omega-K_s)^n(1-F_\theta(\omega-K_s))^{N-n-2}\left[f_\theta(\omega-K_s)^2f_\omega(\omega)\right]\Bigg]\\
&\qquad\int_{\mathbb{R}} f_\theta(\omega-K_s)F_\theta(\omega-K_s)^n(1-F_\theta(\omega-K_s))^{N-n-1}f_\omega(\omega)d\omega\\
&\qquad-f_\theta(\omega-K_s)F_\theta(\omega-K_s)^n(1-F_\theta(\omega-K_s))^{N-n-1}f_\omega(\omega)\\
&\qquad\int_{\mathbb{R}}\Bigg[F_\theta(\omega-K_s)^n(1-F_\theta(\omega-K_s))^{N-n-1}\left[f'_\theta(\omega_i-K_s)f_\theta(\omega-K_s)f_\omega(\omega)\right]\\
&\qquad+nF_\theta(\omega-K_s)^{n-1}(1-F_\theta(\omega-K_s))^{N-n-1}\left[f_\theta(\omega-K_s)^2f_\omega(\omega)\right]\\
&\qquad-(N-n-1)F_\theta(\omega-K_s)^n(1-F_\theta(\omega-K_s))^{N-n-2}\left[f_\theta(\omega-K_s)^2f_\omega(\omega)\right]\Bigg]\Bigg)
\end{aligned}
$$

$$
\begin{aligned}
&\frac{\partial}{\partial K_s}\frac{f_\theta(\omega-K_s)F_\theta(\omega-K_s)^{n-1}(1-F_\theta(\omega-K_s))^{N-n}f_\omega(\omega)d\omega}{\int_{\mathbb{R}} f_\theta(\omega_i-K_s)f_\theta(\omega-K_s)F_\theta(\omega-K_s)^{n-1}(1-F_\theta(\omega-K_s))^{N-n}f_\omega(\omega)d\omega}\\
&\qquad=\frac{-1}{\left(\int_{\mathbb{R}} f_\theta(\omega-K_s)F_\theta(\omega-K_s)^{n-1}(1-F_\theta(\omega-K_s))^{N-n}f_\omega(\omega)d\omega\right)^2}\\
&\qquad\Bigg(\Bigg[F_\theta(\omega-K_s)^{n-1}(1-F_\theta(\omega-K_s))^{N-n}\left[f'_\theta(\omega_i-K_s)f_\theta(\omega-K_s)f_\omega(\omega)\right]\\
&\qquad+(n-1)F_\theta(\omega-K_s)^{n-2}(1-F_\theta(\omega-K_s))^{N-n}\left[f_\theta(\omega-K_s)^2f_\omega(\omega)\right]\\
&\qquad-(N-n)F_\theta(\omega-K_s)^{n-1}(1-F_\theta(\omega-K_s))^{N-n-1}\left[f_\theta(\omega-K_s)^2f_\omega(\omega)\right]\Bigg]\\
&\qquad\int_{\mathbb{R}} f_\theta(\omega-K_s)F_\theta(\omega-K_s)^{n-1}(1-F_\theta(\omega-K_s))^{N-n}f_\omega(\omega)d\omega\\
&\qquad-f_\theta(\omega-K_s)F_\theta(\omega-K_s)^{n-1}(1-F_\theta(\omega-K_s))^{N-n}f_\omega(\omega)\\
&\qquad\int_{\mathbb{R}}\Bigg[F_\theta(\omega-K_s)^{n-1}(1-F_\theta(\omega-K_s))^{N-n}\left[f'_\theta(\omega_i-K_s)f_\theta(\omega-K_s)f_\omega(\omega)\right]\\
&\qquad+(n-1)F_\theta(\omega-K_s)^{n-2}(1-F_\theta(\omega-K_s))^{N-n}\left[f_\theta(\omega-K_s)^2f_\omega(\omega)\right]\\
&\qquad-(N-n)F_\theta(\omega-K_s)^{n-1}(1-F_\theta(\omega-K_s))^{N-n-1}\left[f_\theta(\omega-K_s)^2f_\omega(\omega)\right]\Bigg]d\omega\Bigg)
\end{aligned}
$$

Then

$$
\begin{aligned}
&\frac{\partial Prob[\theta_s|K_s,n+1]}{\partial K_s}-\frac{\partial Prob[\theta_s|K_s,n]}{\partial K_s}>0\\
&\iff \frac{1}{\left(\int_{\mathbb{R}} f_\theta(\omega-K_s)F_\theta(\omega-K_s)^{n-1}(1-F_\theta(\omega-K_s))^{N-n}f_\omega(\omega)d\omega\right)^2}\\
&\Bigg(\Bigg[F_\theta(\omega-K_s)^{n-1}(1-F_\theta(\omega-K_s))^{N-n}\left[f'_\theta(\omega_i-K_s)f_\theta(\omega-K_s)f_\omega(\omega)\right]\\
&+(n-1)F_\theta(\omega-K_s)^{n-2}(1-F_\theta(\omega-K_s))^{N-n}\left[f_\theta(\omega-K_s)^2f_\omega(\omega)\right]\\
&-(N-n)F_\theta(\omega-K_s)^{n-1}(1-F_\theta(\omega-K_s))^{N-n-1}\left[f_\theta(\omega-K_s)^2f_\omega(\omega)\right]\Bigg]\\
&\int_{\mathbb{R}} f_\theta(\omega-K_s)F_\theta(\omega-K_s)^{n-1}(1-F_\theta(\omega-K_s))^{N-n}f_\omega(\omega)d\omega\\
&-f_\theta(\omega-K_s)F_\theta(\omega-K_s)^{n-1}(1-F_\theta(\omega-K_s))^{N-n}f_\omega(\omega)\\
&\int_{\mathbb{R}}\Bigg[F_\theta(\omega-K_s)^{n-1}(1-F_\theta(\omega-K_s))^{N-n}\left[f'_\theta(\omega_i-K_s)f_\theta(\omega-K_s)f_\omega(\omega)\right]\\
&+(n-1)F_\theta(\omega-K_s)^{n-2}(1-F_\theta(\omega-K_s))^{N-n}\left[f_\theta(\omega-K_s)^2f_\omega(\omega)\right]\\
&-(N-n)F_\theta(\omega-K_s)^{n-1}(1-F_\theta(\omega-K_s))^{N-n-1}\left[f_\theta(\omega-K_s)^2f_\omega(\omega)\right]\Bigg]d\omega\Bigg)\\
&-\frac{1}{\left(\int_{\mathbb{R}} f_\theta(\omega-K_s)F_\theta(\omega-K_s)^{n}(1-F_\theta(\omega-K_s))^{N-n-1}f_\omega(\omega)d\omega\right)^2}\\
&\Bigg(\Bigg[F_\theta(\omega-K_s)^{n}(1-F_\theta(\omega-K_s))^{N-n-1}\left[f'_\theta(\omega_i-K_s)f_\theta(\omega-K_s)f_\omega(\omega)\right]\\
&+nF_\theta(\omega-K_s)^{n-1}(1-F_\theta(\omega-K_s))^{N-n-1}\left[f_\theta(\omega-K_s)^2f_\omega(\omega)\right]\\
&-(N-n-1)F_\theta(\omega-K_s)^{n}(1-F_\theta(\omega-K_s))^{N-n-2}\left[f_\theta(\omega-K_s)^2f_\omega(\omega)\right]\Bigg]\\
&\int_{\mathbb{R}} f_\theta(\omega-K_s)F_\theta(\omega-K_s)^{n}(1-F_\theta(\omega-K_s))^{N-n-1}f_\omega(\omega)d\omega\\
&-f_\theta(\omega-K_s)F_\theta(\omega-K_s)^{n}(1-F_\theta(\omega-K_s))^{N-n-1}f_\omega(\omega)\\
&\int_{\mathbb{R}}\Bigg[F_\theta(\omega-K_s)^{n}(1-F_\theta(\omega-K_s))^{N-n-1}\left[f'_\theta(\omega_i-K_s)f_\theta(\omega-K_s)f_\omega(\omega)\right]\\
&+nF_\theta(\omega-K_s)^{n-1}(1-F_\theta(\omega-K_s))^{N-n-1}\left[f_\theta(\omega-K_s)^2f_\omega(\omega)\right]\\
&-(N-n-1)F_\theta(\omega-K_s)^{n}(1-F_\theta(\omega-K_s))^{N-n-2}\left[f_\theta(\omega-K_s)^2f_\omega(\omega)\right]\Bigg]d\omega\Bigg)>0
\end{aligned}
$$

$$
\begin{aligned}
\iff & \frac{F_\theta(\omega-K_s)^{n-2}(1-F_\theta(\omega-K_s))^{N-n-1}}{\left(\int_{\mathbb{R}} f_\theta(\omega-K_s)F_\theta(\omega-K_s)^{n-1}(1-F_\theta(\omega-K_s))^{N-n}f_\omega(\omega)d\omega\right)^2} \\
& \Bigg(\Bigg[F_\theta(\omega-K_s)(1-F_\theta(\omega-K_s))\left[f'_\theta(\omega_i-K_s)f_\theta(\omega-K_s)f_\omega(\omega)\right] \\
& + (n-1)(1-F_\theta(\omega-K_s))\left[f_\theta(\omega-K_s)^2 f_\omega(\omega)\right] \\
& - (N-n)F_\theta(\omega-K_s)\left[f_\theta(\omega-K_s)^2 f_\omega(\omega)\right]\Bigg] \\
& \int_{\mathbb{R}} f_\theta(\omega-K_s)F_\theta(\omega-K_s)^{n-1}(1-F_\theta(\omega-K_s))^{N-n}f_\omega(\omega)d\omega \\
& - f_\theta(\omega-K_s)F_\theta(\omega-K_s)(1-F_\theta(\omega-K_s))f_\omega(\omega) \\
& \int_{\mathbb{R}}\Bigg[F_\theta(\omega-K_s)^{n-1}(1-F_\theta(\omega-K_s))^{N-n}\left[f'_\theta(\omega_i-K_s)f_\theta(\omega-K_s)f_\omega(\omega)\right] \\
& + (n-1)F_\theta(\omega-K_s)^{n-2}(1-F_\theta(\omega-K_s))^{N-n}\left[f_\theta(\omega-K_s)^2 f_\omega(\omega)\right] \\
& - (N-n)F_\theta(\omega-K_s)^{n-1}(1-F_\theta(\omega-K_s))^{N-n-1}\left[f_\theta(\omega-K_s)^2 f_\omega(\omega)\right]\Bigg]d\omega\Bigg) \\
& - \frac{F_\theta(\omega-K_s)^{n-1}(1-F_\theta(\omega-K_s))^{N-n-2}}{\left(\int_{\mathbb{R}} f_\theta(\omega-K_s)F_\theta(\omega-K_s)^{n}(1-F_\theta(\omega-K_s))^{N-n-1}f_\omega(\omega)d\omega\right)^2} \\
& \Bigg(\Bigg[F_\theta(\omega-K_s)(1-F_\theta(\omega-K_s))\left[f'_\theta(\omega_i-K_s)f_\theta(\omega-K_s)f_\omega(\omega)\right] \\
& + n(1-F_\theta(\omega-K_s))\left[f_\theta(\omega-K_s)^2 f_\omega(\omega)\right] \\
& - (N-n-1)F_\theta(\omega-K_s)\left[f_\theta(\omega-K_s)^2 f_\omega(\omega)\right]\Bigg] \\
& \int_{\mathbb{R}} f_\theta(\omega-K_s)F_\theta(\omega-K_s)^{n}(1-F_\theta(\omega-K_s))^{N-n-1}f_\omega(\omega)d\omega \\
& - f_\theta(\omega-K_s)F_\theta(\omega-K_s)(1-F_\theta(\omega-K_s))f_\omega(\omega) \\
& \int_{\mathbb{R}} f_\theta(\omega-K_s)F_\theta(\omega-K_s)^{n}(1-F_\theta(\omega-K_s))^{N-n-1}f_\omega(\omega)d\omega \\
& - f_\theta(\omega-K_s)F_\theta(\omega-K_s)^{n}(1-F_\theta(\omega-K_s))^{N-n-1}f_\omega(\omega) \\
& \int_{\mathbb{R}}\Bigg[F_\theta(\omega-K_s)^{n}(1-F_\theta(\omega-K_s))^{N-n-1}\left[f'_\theta(\omega_i-K_s)f_\theta(\omega-K_s)f_\omega(\omega)\right] \\
& + nF_\theta(\omega-K_s)^{n-1}(1-F_\theta(\omega-K_s))^{N-n-1}\left[f_\theta(\omega-K_s)^2 f_\omega(\omega)\right] \\
& - (N-n-1)F_\theta(\omega-K_s)^{n}(1-F_\theta(\omega-K_s))^{N-n-2}\left[f_\theta(\omega-K_s)^2 f_\omega(\omega)\right]\Bigg]d\omega\Bigg) > 0
\end{aligned}
$$

$$\iff 1 > \frac{F_\theta(\omega - K_s)}{1 - F_\theta(\omega - K_s)} \times \frac{\left(\int_{\mathbb{R}} f_\theta(\omega - K_s) F_\theta(\omega - K_s)^{n-1}(1 - F_\theta(\omega - K_s))^{N-n} f_\omega(\omega) d\omega\right)^2}{\left(\int_{\mathbb{R}} f_\theta(\omega - K_s) F_\theta(\omega - K_s)^{n}(1 - F_\theta(\omega - K_s))^{N-n-1} f_\omega(\omega) d\omega\right)^2}$$

$$\times \Bigg(\Bigg[F_\theta(\omega - K_s)(1 - F_\theta(\omega - K_s)) \left[f'_\theta(\omega_i - K_s) f_\theta(\omega - K_s) f_\omega(\omega) \right]$$

$$+ n(1 - F_\theta(\omega - K_s)) \left[f_\theta(\omega - K_s)^2 f_\omega(\omega) \right]$$

$$- (N - n - 1) F_\theta(\omega - K_s) \left[f_\theta(\omega - K_s)^2 f_\omega(\omega) \right] \Bigg]$$

$$\int_{\mathbb{R}} f_\theta(\omega - K_s) F_\theta(\omega - K_s)^n (1 - F_\theta(\omega - K_s))^{N-n-1} f_\omega(\omega) d\omega$$

$$- f_\theta(\omega - K_s) F_\theta(\omega - K_s)(1 - F_\theta(\omega - K_s)) f_\omega(\omega)$$

$$\int_{\mathbb{R}} f_\theta(\omega - K_s) F_\theta(\omega - K_s)^n (1 - F_\theta(\omega - K_s))^{N-n-1} f_\omega(\omega) d\omega$$

$$- f_\theta(\omega - K_s) F_\theta(\omega - K_s)^n (1 - F_\theta(\omega - K_s))^{N-n-1} f_\omega(\omega)$$

$$\int_{\mathbb{R}} \Bigg[F_\theta(\omega - K_s)^n (1 - F_\theta(\omega - K_s))^{N-n-1} \left[f'_\theta(\omega_i - K_s) f_\theta(\omega - K_s) f_\omega(\omega) \right]$$

$$+ n F_\theta(\omega - K_s)^{n-1} (1 - F_\theta(\omega - K_s))^{N-n-1} \left[f_\theta(\omega - K_s)^2 f_\omega(\omega) \right]$$

$$- (N - n - 1) F_\theta(\omega - K_s)^n (1 - F_\theta(\omega - K_s))^{N-n-2} \left[f_\theta(\omega - K_s)^2 f_\omega(\omega) \right] \Bigg] d\omega \Bigg)^{-1}$$

$$\times \Bigg(\Bigg[F_\theta(\omega - K_s)(1 - F_\theta(\omega - K_s)) \left[f'_\theta(\omega_i - K_s) f_\theta(\omega - K_s) f_\omega(\omega) \right]$$

$$+ n(1 - F_\theta(\omega - K_s)) \left[f_\theta(\omega - K_s)^2 f_\omega(\omega) \right]$$

$$- (N - n - 1) F_\theta(\omega - K_s) \left[f_\theta(\omega - K_s)^2 f_\omega(\omega) \right] \Bigg]$$

$$\int_{\mathbb{R}} f_\theta(\omega - K_s) F_\theta(\omega - K_s)^n (1 - F_\theta(\omega - K_s))^{N-n-1} f_\omega(\omega) d\omega$$

$$- f_\theta(\omega - K_s) F_\theta(\omega - K_s)(1 - F_\theta(\omega - K_s)) f_\omega(\omega)$$

$$\int_{\mathbb{R}} f_\theta(\omega - K_s) F_\theta(\omega - K_s)^n (1 - F_\theta(\omega - K_s))^{N-n-1} f_\omega(\omega) d\omega$$

$$- f_\theta(\omega - K_s) F_\theta(\omega - K_s)^n (1 - F_\theta(\omega - K_s))^{N-n-1} f_\omega(\omega)$$

$$\int_{\mathbb{R}} \Bigg[F_\theta(\omega - K_s)^n (1 - F_\theta(\omega - K_s))^{N-n-1} \left[f'_\theta(\omega_i - K_s) f_\theta(\omega - K_s) f_\omega(\omega) \right]$$

$$+ n F_\theta(\omega - K_s)^{n-1} (1 - F_\theta(\omega - K_s))^{N-n-1} \left[f_\theta(\omega - K_s)^2 f_\omega(\omega) \right]$$

$$- (N - n - 1) F_\theta(\omega - K_s)^n (1 - F_\theta(\omega - K_s))^{N-n-2} \left[f_\theta(\omega - K_s)^2 f_\omega(\omega) \right] \Bigg] d\omega \Bigg)$$

Since $\frac{F_\theta(\omega - K_s)}{1 - F_\theta(\omega - K_s)}$ is the only term in the expression where ω is neither integrated out or identically placed in the numerator and denominator, we know that $\frac{\partial Prob[\theta_s | K_s, n+1]}{\partial K_s} -$

$\frac{\partial Prob[\theta_s|K_s,n]}{\partial K_s} > 0$ holds for smaller values of ω. And as such $\frac{\partial E[\theta_s|a_s,n+1]}{\partial a_s} - \frac{\partial E[\theta_s|a_s,n]}{\partial a_s} \leq 0$.

$\square$

A.3 Experiment Instructions

All experiment sessions were run using Otree. The instructions were shown on a step-by-step basis with each feature of the experiment explained on a sequence of screens.

Instructions: Anticipation Experiment

Screen 1

Hello and welcome, today you will be participating in an experiment on economic decision making. Funds for this experiment have been provided by the University of California. You will be paid for your participation in this experiment. Your final payment will consist of a fixed $5 show-up payment and a $10 completion bonus. You will be paid privately in cash after the experiment has concluded. We ask that you please silence and put away all cell phones and any other personal electronic devices now and for the remainder of the experiment.

In this experiment you will be presented with an opportunity to complete a task for charity. For this project, we are partnering with Dr. James Rolfe – founder of the Afghan Dental Relief Project – to bring modern dental care to the very poor in Afghanistan. The A.D.R.P. is a charitable organization that provides free dental services and dental health education to the poorest families and individuals in the city of Kabul, the capital of Afghanistan. 100% of the donations that you generate from this experiment will be used to purchase dental supplies and ship them to A.D.R.P.'s free dental clinic. Please take the time to carefully read the news article below that details the work Dr. Rolfe and the A.D.R.P. have accomplished and can continue to accomplish with your help.

Screen 2

Today, you will have the opportunity to complete tasks to generate donations to A.D.R.P.'s free dental clinic. The task will be to transcribe captchas. For each task, you will be shown an image of text. Your objective is to correctly type the text that is shown to you in the space provided. Each correctly transcribed captcha will be counted as one completed task. You will have 3 chances to correctly transcribe each captcha. If you fail to correctly transcribe a captcha within three tries you will simply be shown a different captcha. You will now be shown 5 captchas to transcribe so that you are familiar with the task. Please note that each captcha may consist of both capital and lower case letters, the numbers 2-9, and special characters !, %, &, ?.

Screen 3

5 Sample Captchas

Screen 4: Tasks for Donations

For this experiment you will decide how many captchas you are willing to complete in order to generate donations for the A.D.R.P.'s free dental clinic. That is, you will choose the maximum number of captchas you are willing to do for donations of \$2, \$5, \$10, \$15, and \$20. You will be able to select between 0 and 50 tasks for each possible donation amount. For example, if for a donation of \$5 dollars you select 12 tasks, then you are indicating that you are willing to do a maximum of 12 tasks in exchange for a \$5 donation to the A.D.R.P.

After you have made your decisions we will randomly assign each person a donation amount and a number of tasks. If the the number of tasks you are assigned is fewer than the maximum number you selected for yourself, then you will complete your assigned number of tasks and we will give the assigned donation to the A.D.R.P. If the randomly assigned number of tasks is higher than your chosen number, then you will complete no tasks and no donation will be given to the A.D.R.P.

For example, suppose that for a donation of \$15 you choose to do at most 30 tasks. Then if you are randomly assigned \$15 and 20 tasks, then you will complete 20 tasks and \$15 will be given to the Afghan Dental Relief Project. On the other hand if you are randomly assigned \$15 and 40 tasks, then you will do 0 tasks and no donation will be given to the A.D.R.P.

Each person will be assigned their own number of tasks and their own donation amount. No one will learn your assigned donation amount or number of tasks. Please note that the randomization device is “fair” – all possible donation and task amounts will have equal probability of being assigned. So it is in your best interest to treat each decision as if it is the one that counts.

You will be free to leave the experiment as soon as you complete your tasks. You will be free to go immediately if you have no tasks to complete. Your completion bonus will be \$10 regardless of the number of tasks you have to do.

Comprehension Questions

Suppose you choose to do a maximum of 30 tasks for a \$10 donation. Under which of the following conditions would you complete tasks for a \$10 donation?

- If I am randomly assigned a \$10 donation and 20 tasks.
- If I am randomly assigned a \$10 donation and 40 tasks.

Suppose you are assigned a \$10 donation and 21 tasks. How many tasks will you be asked to do?

- 21 if I choose more than 21 tasks for a \$10 donation.
- 21 if I choose fewer than 21 tasks for a \$10 donation.

Suppose you are assigned a \$5 donation and 15 tasks. How many tasks will you be assigned to do?

- 0 if I choose more than 15 tasks for a \$10 donation.
- 0 if I choose fewer than 15 tasks for a \$10 donation.

Screen 5: Guessing other's choices

In addition to selecting how many tasks you are willing to do for each possible donation amount, you will guess how your decisions compare to the decisions of previous participants. That is, you will guess what percent of previous participants were willing to do a larger number of tasks than you for each possible donation. Specifically, you will say whether you believe that at least 95%, 75%, 50%, 25%, or 0% of all previous participants were willing to do more tasks than you.

As an example, suppose that for a donation of $5 dollars you choose to do a maximum of 12 tasks and think that at least 50%, but fewer than 75%, of previous participants were willing to do more than 12 tasks for a $5 donation. Then you will indicate that you believe that at least 50% of all previous experiment participants were willing to do more tasks than you for a $5 donation.

Comprehension Question

Suppose that you choose to do at most 10 tasks for a donation of $15 dollars and that you believe that at least 75%, but fewer than 95%, of previous participants were willing to do more than 10 tasks for a $15 donation. How would you answer the question "What percent of previous participants were willing to do more tasks that you?"

- 95%
- 75%
- 50%
- 25%
- 0%

Screen 5B: Seeing other's choices (Treatment Only)

Lastly, you will learn how your decisions actually compare to the decisions of all those who participated in this experiment before you. After everyone has made their decisions and guesses, you will open the yellow envelope on your desk. The contents of this envelope will show you how many tasks at least 95%, 75%, 50%, 25% and 0% of all previous participants willing to do. Therefore, you will learn the true proportion of previous participants that were willing to do more tasks than you. You will then verify that you understand this information by answering a series of multiple choice questions. Please do not open these envelopes until you are instructed to do so.

For example, suppose for a donation of $5 dollars you were willing to do 12 tasks. And suppose that the information in the yellow envelope shows you that 50% of previous participants were willing to do at least 15 tasks for a $5 donation and 75% were willing to do at least 10 tasks for $5 donation. This would mean that at least 50%, but less than 75%, of previous participants were willing to do more tasks than you for a $5 donation.

Comprehension Question

Suppose that you choose to do at most 35 tasks for a donation of $15 dollars. Also suppose you learn from the information in the yellow envelope that 50% percent of other participants were willing to at least 30 tasks for a $15 donation and 25% were willing to at least 40 tasks for $15 donation. Then what percent of previous experiment participants were actually willing to do more tasks than you?

- 95%
- 75%
- 50%
- 25%
- 0%

Screen 6: Summary

To sum up, the experiment proceeds as follows.

Step 1 You will choose how many tasks you are willing to do for each possible donation amount and you will guess what percent of people were willing to do more tasks than you for each of your decisions. You will do this with sliders and multiple choice questions as shown below. *In Baseline:*In this session – as with 50% of all sessions – you *will not* learn any information on what others actually chose. (*In Treatment:*In this session – as with 50% of all sessions – you *will* learn any information on what others actually chose.)

Step 2 Each person will be randomly assigned a donation amount by drawing a ball out of a jar. A random number generator will then assign you a number of tasks. If this number of tasks is lower than the amount you were willing to do, then you will complete those tasks and we will donate to the A.D.R.P. on your behalf. The experiment will conclude after you finish your tasks (if any). We will hand you your show-up fee and completion bonus ($15) as you exit the lab.

Instructions: Signal Extraction

Screen 1

Hello and welcome, today you will be participating in an experiment on economic decision making. Funds for this experiment have been provided by the University of California. You will be paid for your participation in this experiment. Your final payment will consist of a fixed $5 show-up payment and a $10 completion bonus. You will be paid privately in cash after the experiment has concluded. We ask that you please silence and put away all cell phones and any other personal electronic devices now and for the remainder of the experiment.

In this experiment you will be presented with an opportunity to complete a task for charity. For this project, we are partnering with Dr. James Rolfe – founder of the Afghan Dental Relief Project – to bring modern dental care to the very poor in Afghanistan. The A.D.R.P.

is a charitable organization that provides free dental services and dental health education to the poorest families and individuals in the city of Kabul, the capital of Afghanistan. 100% of the donations that you generate from this experiment will be used to purchase dental supplies and ship them to A.D.R.P.'s free dental clinic. Please take the time to carefully read the news article below that details the work Dr. Rolfe and the A.D.R.P. have accomplished and can continue to accomplish with your help.

Screen 2

Today, you will have the opportunity to complete tasks to generate donations to A.D.R.P.'s free dental clinic. The task will be to transcribe captchas. For each task, you will be shown an image of text. Your objective is to correctly type the text that is shown to you in the space provided. Only correctly transcribed captchas will be counted as completed tasks. You will have 3 chances per captcha. You will now be shown 5 captchas to transcribe so that you are familiar with the task. Please note that each captcha may consist of both capital and lower case letters, only the numbers 2-9, and special characters !, %, &, ?.

Screen 3

5 Sample Captchas

Screen 4: Tasks for Donations

For this experiment you will decide how many captchas you are willing to complete in order to generate a donation for the A.D.R.P.'s free dental clinic. That is, you will choose the maximum number of captchas you are willing to complete in exchange for a donation of $20. You will be able to select between 0 and 50 tasks.

After you have made your decisions we will randomly assign each person a number of tasks. If the the number of tasks you are assigned is fewer than the maximum number you selected for yourself, then you will complete your assigned number of tasks and we will donate to A.D.R.P. on your behalf. If the randomly assigned number of tasks is higher than your chosen number, then you will complete no tasks and no donation will be given to the A.D.R.P.

For example, suppose that you choose to do at most 25 tasks. Then if you are randomly assigned 20 tasks, then you will complete 20 tasks and $20 will be given to the Afghan Dental Relief Project. On the other hand if you are randomly assigned 40 tasks, then you will do 0 tasks and no donation will be given to the A.D.R.P.

Each person will be assigned their own number of tasks. No one will learn your assigned number of tasks. Please note that the randomization device is "fair" – all possible task amounts will have equal probability of being assigned.

You will be free to leave the experiment as soon as you complete your tasks. You will be free to go immediately if you have no tasks to complete. Your completion bonus will be $10 regardless of the number of tasks you have to do.

Identical Comprehension Questions for this section as the Anticipation Experiment

Screen 5: Seeing Other's Choices

In addition to making your own choices, you will receive information about how your decisions compare to the decisions of the over 200 UCSD students who have already participated in this experiment. Before making your decisions, you will each draw an envelope at random. In each of the envelopes will be one of the two following statements on how many tasks previous participants were willing to complete in exchange for a $20 donation to the A.D.R.P. The statements you could receive are:

- More than 50% of all previous participants were willing to do at least 20 tasks.
- Less than 25% of all previous participants were willing to do at least 20 tasks.

In Baseline: Only one of these statements is true. There are a total of 16 available envelopes at the front of the room. 8 of these envelopes contain the true statement and 8 envelopes contain the false statement. Therefore, when you pick an envelope, there will be a 50% chance that you will receive the true statement and a 50% chance that you will receive the false statement.

In Treatment: Only one of these statements is true. There are a total of 16 available envelopes at the front of the room. 15 of these envelopes contain the true statement and 1 envelope contains the false statement. Therefore, when you pick an envelope, there will be a 94% chance that you will receive the true statement and a 6% chance that you will receive the false statement.

Comprehension Questions, Set A

If 8-out-of-16 (*In Treatment:*15-out-of-16) available envelopes contain the true statement, which of the following is most likely going to happen?

- I will receive the true statement.
- I will receive the false statement.
- I will receive the true or false statement with equal probability.

Suppose that you receive the statement that "more than 50% of all previous participants were willing to do at least 20 tasks." What is the probability that this statement is TRUE and that *more than 50%* of all previous participants were willing to do at least 20 tasks?

- 94%
- 50%

Suppose that you receive the statement that "more than 50% of all previous participants were willing to do at least 20 tasks." What is the probability that this statement is FALSE and that *less than 25%* of all previous participants were willing to do at least 20 tasks?

- 50%
- 6%

Comprehension Questions, Set B

If 8-out-of-16 (*in treatment:*15-out-of-16) available envelopes contain the true statement, what is the probability you will receive a true statement?

- 94%
- 50%

If 8-out-of-16 (*in treatment:*15-out-of-16) available envelopes contain the true statement, what is the probability you will receive a false statement?

- 50%
- 6%

If 8-out-of-16 (*in treatment:*15-out-of-16) available envelopes contain the true statement, what is the maximum number of true statements 12 participants could pick?

- 8
- 12

If 8-out-of-16 (*in treatment:*15-out-of-16) available envelopes contain the true statement, what is the maximum number of false statements 12 participants could pick?

- 8
- 1

We switched from comprehension question set B to A after the first few sessions of the signal extraction experiment. We believed set A would be more revealing of subject comprehension. The sessions with question sets A and B are balanced across treatments, and we found no difference in task choice dynamics between comprehension set A and B.

A.4 News Article about the A.D.R.P.

Afghan Dental Relief Project Ready for Next Level[23]
By Kelsey Abkin

In 2003, Santa Barbara dentist James Rolfe came across an article about three women going to Afghanistan to treat victims of PTSD (post-traumatic stress disorder). Instead of putting the article down and going on with his day, Dr. Rolfe picked up the phone and asked to go along. The poverty and vulnerability he saw upon arriving in Afghanistan affected him immediately. Within a country of some 30 million people, Rolfe said he saw "resources in manpower and [natural] resources but no infrastructure to really use it." Eleven years later, thanks to Rolfe and his Afghanistan Dental Relief Project, this is changing. The project started the Kabul Dental Clinic and Training Center, which offers basic dental services, and Rolfe is on the verge of expanding to a permanent dental clinic, hoping to extend nonbasic, often life-saving dental procedures.

The mission began when Rolfe returned to Afghanistan, this time with a homemade, portable dentists office and base camp. Before that, what passed for dental care in the war-torn country often amounted to a barber ripping out sore teeth without anesthetics. With 90 percent of Afghans having never seen a real dentist and 70 percent malnourished, dental problems were extreme. Abscesses were not uncommon and often led to septicemia, which can be lethal without antibiotics. Word that an American dentist had come offering free dental care spread fast among rural communities, and soon Rolfe was helping more than 60 people a day. Many of the orphaned boys whom Rolfe treated would become his assistants, thus leading to the Kabul School of Dental Technology.

After a car bomb, two scams, 100,000 patients treated, and 11 years since the birth of the Afghanistan Dental Relief Project, Rolfe is on the brink of taking it to a new level. He recently worked with Afghanistans Ministry of Public Health to obtain permits to provide more complex, nonbasic dental services to Afghans for a small fee, such as endodontic treatment or prosthetic restorations. For non-Afghans, however, the fee is equivalent to what they would pay in Dubai, and the treatment of only 16 non-Afghans covers the clinics entire monthly operating expenses.

Today, Rolfe can be found in his successful dentistry clinic near the Lobero Theatre. His self-built office surrounds his patients with the sounds of nature and artifacts reminiscent of a cultured life. He has managed to live a life performing dentistry for no cost in a Santa Barbara commune and now helping thousands in Afghanistan that intertwines his passion to help with his skills as a dentist. Rolfe, who is 75 years old, continues to work 115 hours a week and lives well below the poverty line. Except for his basic needs, he gives all he makes to his Afghanistan project, and hes nowhere near ready to slow down. In the future, he sees a first-rate dental infrastructure providing Afghans with health care, jobs and education. "We need to be more active," Rolfe said. "If we feel something in our heart, we need to act on that, and that needs to form the basis of our existence."

[23]This is an abridged version of an article in the *Santa Barbera Independent* from 2014. This the the text that was shown to subjects. The full-legnth article can be found here: https://www.independent.com/news/2014/jul/12/afghan-dental-relief-project-ready-next-level/