# Knowing When to Leave Someone Isn't Easy:
# Social Foraging with Partners of Varying Cooperation Levels

By

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Thesis

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This thesis by William Lee is accepted in its present form by the Department of Cognitive, Linguistic, and Psychological Sciences as satisfying the thesis requirement for the degree of Master of Science

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Oriel FeldmanHall Ph.D., Advisor

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Andrew G. Campbell, Dean of the Graduate School

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# Table of Contents

## Introduction

It is hard not to think about the "What Ifs" in life. From the relationships we had in the past, to the jobs we passed up, humans have a tendency to compare their current options to numerous alternatives that could have been experienced (Coricelli & Rustichini, 2010). One example is maintaining a fading long-distance friendship. Do you continue the friendship despite the diminishing quality? Partnerships and relationships require us to compare the value of staying with a current partner against the value of leaving for an unknown, perhaps better, option. This can often be difficult to assess, since there are many social influences (e.g., the cooperativeness, kindness, trustworthiness of our partner can vary) that make it unclear whether it is optimal to continue the friendship or leave for potentially greener pastures.

This broader question has been well researched in one branch of ecology known as foraging. Much work has examined how non-human animals decide to continue exploiting a known resource (e.g., consume berries from a specific bush) versus exploring for a potentially better resource (e.g., search for another bush that may contain more berries). Animals make these decisions by estimating the average reward in the environment (i.e., average number of berries found on bushes in the environment) and comparing this long-running average to their current resource patch. Critically, an animal's current resource patch has a diminishing return such that over time, the berry bush becomes less plentiful and the value of searching for a new resource becomes more tempting. In short, foraging theory primarily measures an animal's ability to optimally estimate the value of staying or leaving a specific resource patch for another, perhaps, more bountiful patch (Charnov, 1976). The field of ecology has popularized the Marginal Value Theorem (MVT), which measures the optimal departure time (minimum amount reward needed at a given time to make exploitation worth forgoing the potential value of exploration) when the current value of staying is equal to or less than the value of leaving (accounting for the cost of finding a new resource). Studies on dung flies (Parker, 1978 & 1992) and birds (Cowie, 1977), for example, reveal that the MVT can identify how, and when, animals employ reward maximizing behavior.

Ecology research has also illustrated numerous environmental factors that have caused animals to violate optimal foraging theory (Stephens, 2007; Huey, & Pianka, 1981). For example, increases in predators or resource scarcity can shift an animal's behavior to over-exploit a resource beyond the optimal departure threshold (Frid, Burns, Baker, & Thorne, 2009, Pyke, 1980). These environmental fluctuations cause uncertainty and stress for the animal, making it more difficult to identify and follow an optimal choice policy.

Research on foraging choices in humans (also known as stay-or-leave decision making), has also revealed that humans can compute the optimal departure time in agricultural contexts, such as foraging for apples in an orchard (Hayden, 2011; Daw, O'Doherty, Dayan, Seymour, & Dolan, 2006; Shenhav, Straccia, Cohen, & Botvinick, 2014 & 2016; Kolling, Wittmann, & Rushworth, 2014; Kolling, Wittmann, Behrens, Boorman, Mars, Rogier, & Rushworth, 2016). The tasks used in these experiments test the MVT by having subjects choose between shaking a tree for apples (exploit) or searching the environment for a new replenished resource (explore). While these paradigms consistently identify mechanisms that drive optimal and suboptimal foraging behavior (Constantino & Daw, 2015), they fail to be good testbeds for human foraging behavior because of the lack of consideration towards social factors.

The overwhelming majority of decisions humans make are social in nature, which introduces an entirely new set of tensions that had yet to be explored under classic foraging approaches. An open question is whether documented foraging mechanisms also function in similar ways in social contexts, such as weighing up the cost-benefits of staying in a relationship or leaving to find a potentially better one.

To answer this question, we created a novel social foraging task where subjects were required to work with other people to collectively pay off a monetary debt. In some contexts, there were many potential social partners who contributed equally to paying off the debt. In other contexts, there were very few social partners who contributed an equal share. This experimental design allowed us to vary the average cooperation level of each potential relationship (the amount partners contribute to the debt), as well as the type of environment (abundant versus scarce) to answer two critical questions: (1) Did a partner's cooperation level and quality of an environment influence deviations from optimal foraging behavior? (2) Was suboptimal behavior (i.e. over-exploitation) better characterized by inaccurate estimates of the optimal exit strategy (when to stay/leave a partnership) or by noisy behavior (i.e. treating partners differently based on the cooperation level and scarcity of the environment)?

Based on previous work, we hypothesized that 1) social traits such as cooperation level (Hackel, Doll, & Amodio, 2015) would influence subjects to weight the reward received from typical cooperative partners more highly than equivalent rewards from typical defectors; 2) subjects' preferences for over-exploitation would be motivated by the quality of the environment they were played in (Lenow et al. 2017); and 3) these sub-optimal choices would be the result of inaccurate estimations of the value of leaving a partnership and the inability to stick to a consistent decision-making strategy.

## Methods

### Subjects

85 subjects, ages 18-24 were recruited through Sona Systems, Brown University's student and community subject pool for psychological experiments. Subjects were compensated a base amount of either $10/hour or 1 course credit and a monetary bonus (maximum of $6) based on task performance. Subjects had the choice to elect either form of compensation prior to the experiment. In total, five subjects were removed from the final sample either due to incomplete data (N=3) or misunderstanding the instructions of the task (N=2). Thus, the final sample for the study comprised of 80 subjects (mean age= 20.23, SD+- = 1.44; 57 females). All data was gathered under our Brown University's Institutional Review Board's approved protocol.

### Social Foraging Task

Subjects played a novel social foraging task. At the beginning of the task, subjects were told that they would be playing an economic decision-making task with past subjects who came into the lab and took a similar experiment. At the start of the game, subjects were matched with a player and told they would be working with them to allocate points towards a threshold to pay off a debt. The debt needed to be collectively paid with a partner, and both players would use some of their points to help reach the threshold.

At the start of each round, of which there were 100, the subject and partner were both endowed with 100 points (Figure 1A). On the first round, subjects were required to play with their partner to meet the threshold. Subjects were then shown the amount of points their partner had allocated towards the threshold and were forced to contribute the remaining points needed to reach the threshold (the contributed points were subtracted from their total points; Figure 1B). As a reward for meeting the threshold, the subject and partner were each awarded 20 points which was added to both people's running point total (Figure 1C).

Before starting the next round, the subject was notified that the threshold would be increased by 10 points (i.e., become 110 on the second round) if they chose to stay with the same partner (Figure 1D). Subjects were then asked whether they wanted to continue playing with their partner (e.g. exploit) or search for a different partner to play with (e.g. explore), where there was a 30% chance of successfully being matched (Figure 1E). If they failed to find a partner, they lost one trial and received 0 points (instead of the 100-point endowment if they had a partner). Furthermore, subjects continued searching for a partner until they were successfully matched.

When subjects chose to stay with their current partner, they committed to play one additional round with them. Although they knew the threshold was higher, they did not know with how many points their partner would be contributing that round. Regardless of the amount someone's partner had contributed, subjects were always required to pay the difference that was needed to reach the threshold. Subjects had 100 rounds to accumulate points, which, at the end of the experiment, would be converted into a monetary bonus at a rate of $1 for every 2000 points earned.

**Procedure**

At the start of the experiment, subjects were instructed on the details of the social foraging game and told they would be playing with past subjects who had completed a similar task. To enhance believability, a picture was taken of the subject with the preface that the photo and choices they made would be used in future studies. Afterwards, subjects were informed that the bonus paid out depended on the choices made during the task. After completing the social foraging task, subjects provided information on their demographics, ability to tolerate uncertainty (Buhr & Dugas, 2002), and tendency towards impulsivity (Kirby, Petry, & Bickel, 1999). Subjects were then debriefed and notified that deception was used.

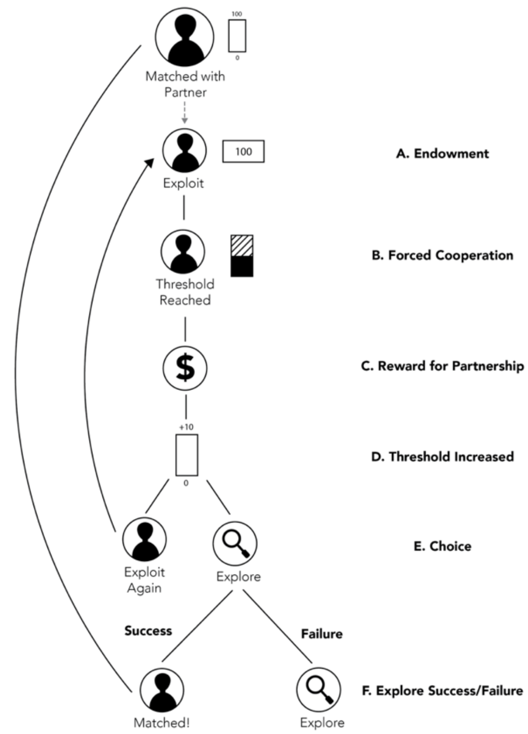


**Figure 1**. *The task schematic of the social foraging paradigm subjects played outlines the key components of the game. A) Subjects and their partners were given 100 points each. B) Once subjects commit to playing with their partner they must fill in the remaining threshold necessary. C) Both subjects and their partners receive 20 points for reach the threshold. D) The threshold increases by 10 points for the next round. E) Subjects chooses to search for play with current partner or search for a new one. F) Failure to find a partner forces subject to keep searching till a new partner was found.*

*Measuring Subjects' Fairness Level*

To get a better understanding of how cooperative our subjects would be if they were the partners in this task, subjects completed a shorter version of the task as the matched partner. They were asked to make the first contribution prior to their partner's required contribution, which allowed us to measure our subjects' baseline willingness to cooperate (Figure 2). This allowed us to calculate the average cooperation levels in our sample. Subjects played 5 rounds of this game with 3 different hypothetical players for a total of 15 first mover responses.

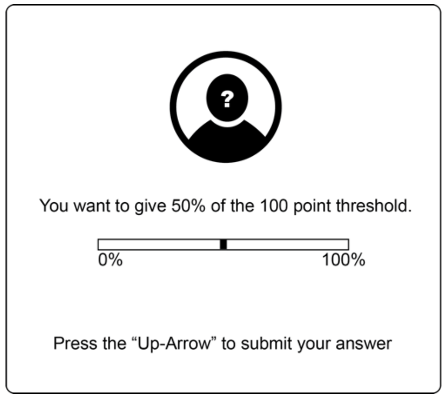


***Figure 2***. *Subjects indicated the proportion of the threshold they would have given if they were the first person to contribute points in the task.*

*Prediction of Partner's Level of Cooperation*

Every time a subject was matched with a new partner, they were asked to predict the proportion of the threshold their partner would contribute (on a 0-100% scale). These predictions were used to get a measure of a subject's perception of the average cooperation level of the environment and determine whether it deviated from the true average cooperation level of the environment.

*Experimental Conditions*

Before starting the task, subjects were informed of the average cooperation level of the partners in the environment. Each environment, of which there were three, has five different player types ranging from low cooperation (contributing 30% towards the threshold) to high cooperation partners (contributing 50% towards the threshold). Partners' contributions were noisy (noise rate had a standard deviation of 1%), such that partners who typically contributed 50% towards the threshold might on some trials give 49% and on other trials 51%.

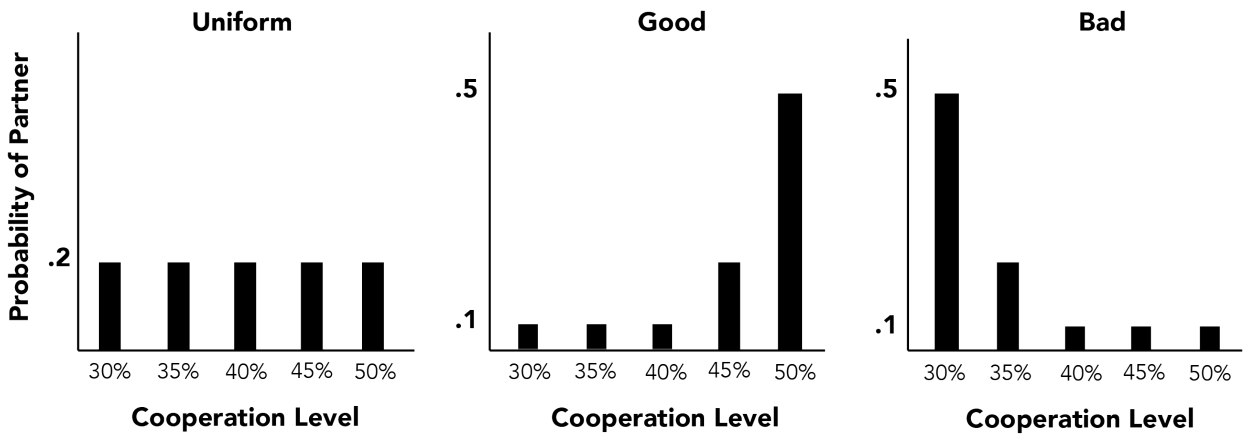


***Figure 3****. There were three types of environmental manipulations that a subject could experience that differed depending on the condition the subject was assigned to. The different environments manipulated the spread of player types in an environment or the probability of encountering specific types of players. In the good-skewed environment, you had a 50% chance of finding a high cooperation partner (gives 50% of the threshold) while the bad skewed environment gives you a 50% chance of finding a low cooperation partner (gives 30% of the threshold).*

The environment's cooperation level manipulated the probability of encountering good and bad player types (Figure 3). In a uniform environment, there was an equal chance of encountering any player type. Good and bad environments shifted the distribution of these probabilities to favor high and low cooperation players, respectively.

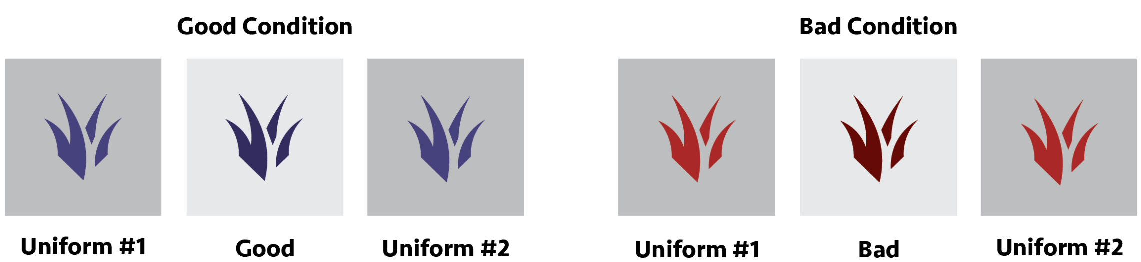


***Figure 4****. The Social Foraging Task had 2 different conditions. Subjects that played in the good condition played 2 games of a uniform environment and one in a good environment, while the bad condition subjects played 2 games of a uniform environment and one in a bad environment.*

Subjects were randomly assigned to be in either the good of bad environment. If a subject was assigned to the good environment, they first played a social foraging task in a uniform environment, then an iteration of the task in a good environment where there were many highly cooperative players, and a final iteration of the task in a uniform environment. This allowed us to examine whether being exposed to a good or bad environment had any lasting effects on how potential partners were treated. This design explored whether the skew of an environment affects foraging behavior to accommodate the cooperative or uncooperativeness of such an environment.

*Intolerance to Uncertainty & Intertemporal Choice Scales*

In our social foraging task, players made decisions to leave immediate rewards for potential future rewards that would be accrued from working with new partners. Thus, collecting a measure of impulsiveness was necessary to understanding how willingness to delay gratification may be attributed to a preference for selecting immediate rewards over potentially larger ones in the future. To measure subjects' impulsive nature, we gathered their responses to the Intertemporal Choice Scale (ITC; Kirby, Petry, & Bickel, 1999), a measure of willingness to delay gratification by asking 27 questions, such as "would you rather receive $54 today or $55 in 117 days?". Subjects indicated their preference for either the immediate or delayed reward.

We also collected a measure of intolerance to uncertainty. Past research on uncertainty and stress demonstrates that changes in uncertainty can motivate behavior change (Mazur, 2004). Thus, intolerance to uncertainty may be a candidate mechanism that determines decisions to stay or leave in social foraging task. Subjects' intolerance to uncertainty was captured using the Intolerance to Uncertainty Scale (IUS; Buhr & Dugas, 2002), a scale consisting of 27 questions that ask subjects how specific scenarios with associated levels of uncertainty relate to them. For example, a question might ask whether "Uncertainty stops me from having a firm opinion." on a scale from 1 = not characteristic of me, to 5 = entirely characteristically of me.

## Analysis

*Measuring optimal foraging:*

According to the MVT, the optimal decision rule (i.e., the decision rule that maximizes the long-running average reward rate) is to leave when the expected number of resources (e.g., apples) from the current patch is smaller than the average number of resources expected in the environment. Research on human foraging has validated proofs of the MVT and is developing models to predict the exact long run average of specific environments (Lenow et al., 2017; Constantino & Daw, 2015).

While past research adapted models from the ecology literature (Constantino & Daw, 2015), the specific formulation of these models cannot be applied in the present study because they used a fixed depletion rate of resources (e.g., number of apples that decreases over time). In these models, the fixed decay rate is multiplied by the current reward to estimate the reward for the following round. In our social foraging task, the decay rate *exponentially increased* over time, which makes adapting these optimal value models ill-equipped for our purposes. Therefore, we took a different approach to estimate the optimal departure time in our task which still followed the same principles and conventions of MVT (Charnov, 1976).

To calculate an optimal choice rule, we simulated all possible exit strategies (i.e., the choice rule that specified which reward rate to leave the current partner). We then ran 100,000 simulations to determine which exit strategy (departure threshold) maximized a player's average reward. Due to the exponential decay rate of our task, we predicted that we would find a cluster of similar exit strategies that would maximize average reward. These predictions were validated in our simulation (Figure 5) and used as an objective measure to estimate subject's deviation from optimality.

A single value of optimality in each environment was identified by taking the mean value of the best strategy clusters (strategies circled in red in Figure 5). Because these exit strategies earned approximately the same amount of average reward per trial, taking the mean is an unbiased way of determining optimality.

Deviations from optimality were calculated by taking the mean optimal exit strategy of the environment (e.g., 38.5 in the uniform environment) and comparing it to the reward a subject received on a given trial. Trials were defined as over-exploit trials if a subject continued to stay with their current partner after receiving a reward that was lower than the optimal exit strategy reward. For example, if the total reward a subject earned is less than 38.5 on a given round in the uniform environment and the subject subsequently chose to continue playing with their partner, we defined their behavior as over-exploiting. Trials were determined to be under-exploit trials if a subject left their current partner before receiving a reward that was lower than the optimal exit strategy reward. Using these measures, we examined how many trials on average subjects over or under-exploited partners with varying cooperation levels.

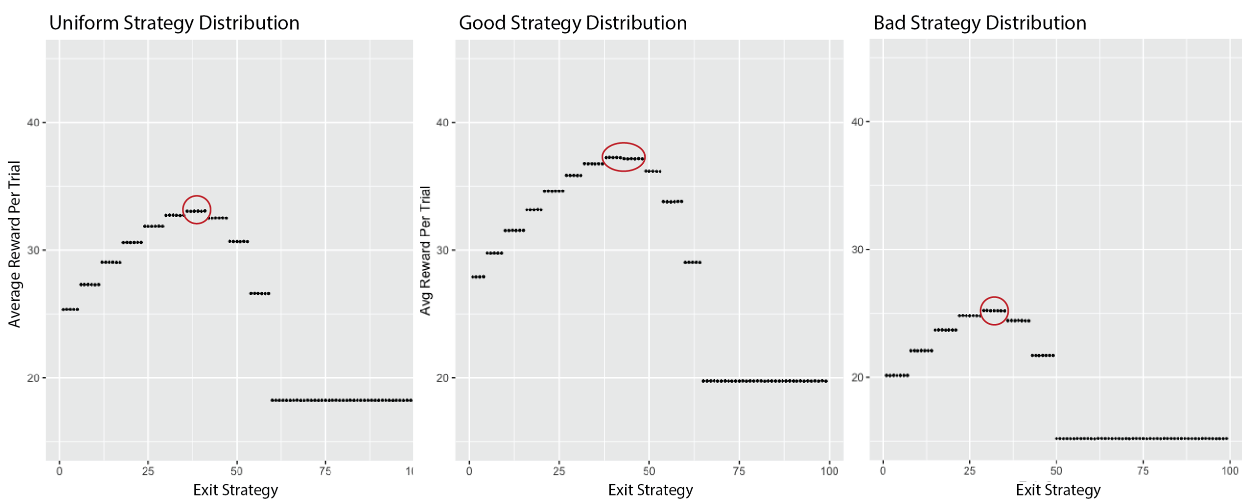


***Figure 5*. *Simulation to Find the Optimal Choice Rule*.** *Numerical optimization was used find the optimal threshold for each environment in our task. The optimal exit strategies for the uniform, good and bad environment were 38.5, 43, and 32 respectively.*

**Results:**

Our main variable of interest in the social foraging task was how many trials subjects over or under-exploited their partners (i.e., number of trials deviating from optimality). Analyses were also computed using estimated reward thresholds (i.e., an estimated exit strategy per subject) but these results mirrored each other. Our analyses used a hierarchical design to ensure that any randomness in the subjects' environment (e.g., a subject might take a long time to find a new partner due to random chance) was controlled for.

*Preference for Over-Exploitation:*

We first examined how optimal people's choices were in our social foraging paradigm. A one sample t-test comparing all subjects' behavior to the optimal threshold for all environments showed that people significantly over-exploited (M = 2.372, SD = 2.800, $t(79) = 7.577$, $p < 0.001$). Further probing subjects' behavior revealed consistent evidence of over-exploitation for every phase of the task (Table 1). If nonsocial foraging bears a one-to-one correspondence with social foraging, we would expect that people would behave optimally in our task. However, our results showed that people had a tendency to over-exploit in social contexts.

**Table 1. People Over-Exploit in Social Foraging**

| Dependent variable | Mean | t | p |
|---|---|---|---|
| Over-Exploitation | | | |
| Good Uniform #1 | 2.47 | 5.14 | <.001*** |
| Good Experimental | 2.95 | 5.76 | <.001*** |
| Good Uniform #2 | 2.48 | 5.53 | <.001*** |
| Bad Uniform #1 | 2.53 | 4.44 | <.001*** |
| Bad Experimental | 1.47 | 3.29 | <.002** |
| Bad Uniform #2 | 2.39 | 5.57 | <.001*** |

*Note.* One-Sample t-tests against 0 for each phase.
** p < .01.    *** p <.001.

*Environmental scarcity decreases exploitation while environmental abundance increases exploitation.*

We next examined how changes in the environmental quality (i.e., amount of cooperative versus uncooperative partners) changed subjects' behavior in our social foraging task. While environmental manipulations in nonsocial environments can predict over-exploitation when the environment has scarce resources (Lenow et al. 2017; Frid, Burns, Baker, & Thorne, 2009), our results indicated the opposite. We first analyzed the results from participants in the bad condition, where subjects played three phases which varied distribution of partners: first uniform, bad environment, and finally a second uniform. Using a linear mixed effects regression examining choice predicted from phases, we found that subjects in the bad condition performed closer to optimal when partners were overall uncooperative (bad environment) than either uniform environments (Table 3). In other words, when the environment is skewed to have mostly uncooperative partners, subjects adjusted their behavior to be more optimal (Figure 6). The same analysis was run for subjects in the good condition (where the three phases are first uniform, good environment, and second uniform), revealing that subjects significantly deviated from optimal behavior in good environments (Table 2). This means that when partners were generally cooperative, subjects stayed relatively longer (over-exploited) with these partners than partners in either uniform environments. Overall, these results revealed that subjects' evaluation of their partners were shaped by the environment, but not in the manner predicted by the nonsocial foraging literature.

**Table 2. Subjects Over-Exploit More in the Good Environment**

$$Over - Exploitation_{i,t} = \beta_0 + \beta_1 Phase_{i,t} + \varepsilon$$

| Independent Variable | Estimate (SE) | t | p |
|---|---|---|---|
| Intercept | 2.94 (0.46) | 6.37 | <0.001*** |
| Phase (Uniform #1) | -0.52 (0.25) | -2.06 | 0.039* |
| Phase (Uniform #2) | -0.44 (0.25) | -1.78 | 0.0762 |

*Note.* Over-Exploitation ~ Phase, where the good environment is the reference category. Over-Exploitation is defined as number of trials beyond the optimal leave point. The model included a random intercept and slope for phase for each subject.
* p < .05. ** p < .01. *** p <.001.

**Table 3. Subjects Over-Exploit Less in the Bad Environment**

$$Over - Exploitation_{i,t} = \beta_0 + \beta_1 Phase_{i,t} + \varepsilon$$

| Independent variable | Estimate (SE) | t | P |
|---|---|---|---|
| Intercept | 1.51 (0.47) | 3.20 | 0.002** |
| Phase (Uniform #1) | 0.99 (0.25) | 3.90 | <0.001*** |
| Phase (Uniform #2) | 0.85 (0.25) | 3.36 | <0.001*** |

*Note.* Over-Exploitation ~ Phase, where the bad environment is the reference category. Over-Exploitation is defined as number of trials beyond the optimal leave point. The model included a random intercept and slope for phase for each subject.
* p < .05. ** p < .01. *** p <.001.

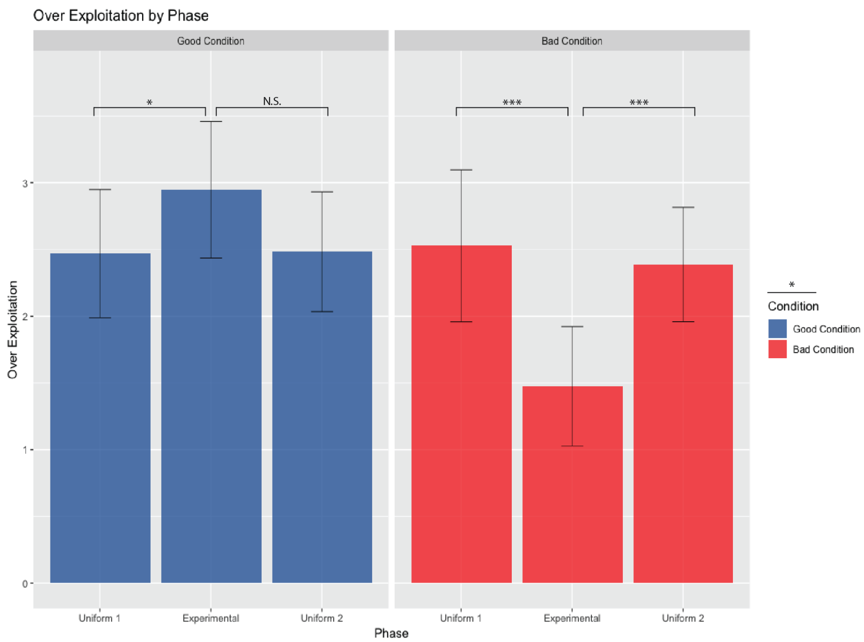


***Figure 6. Scarce Environments Reduce Over-Exploitation.*** *Deviations from optimality (0) by phase and condition. This suggests that players over-exploit more in good environments and less in bad environments.*

*People exploit cooperative partners:*

Past research examining how social traits change behavior (Hackel et al., 2015) demonstrates that people deeply value social traits independently of how rewarding certain actions might be (e.g., valuing generosity when distributing resources independent of the goods received). In our task, this implies that the degree of cooperation a partner displays should increase their value to subjects beyond the monetary reward their cooperation brings. To test this hypothesis, we included player type in our analyses (Figure 7) and examined subjects' behavior using linear mixed effects regressions. Choices in both the good and bad conditions revealed a significant main effect of the cooperativeness of partners (i.e., player type) such that subjects were more likely to over-exploit cooperative partners compared to uncooperative partners (see table 4). While subjects over-exploited all partners in general, the significant effect of player type in both conditions illustrated that subjects over-exploited relatively more with cooperative partners. These results supported our predictions that people overweight social traits such as cooperativeness when making decisions to stay or leave a relationship.

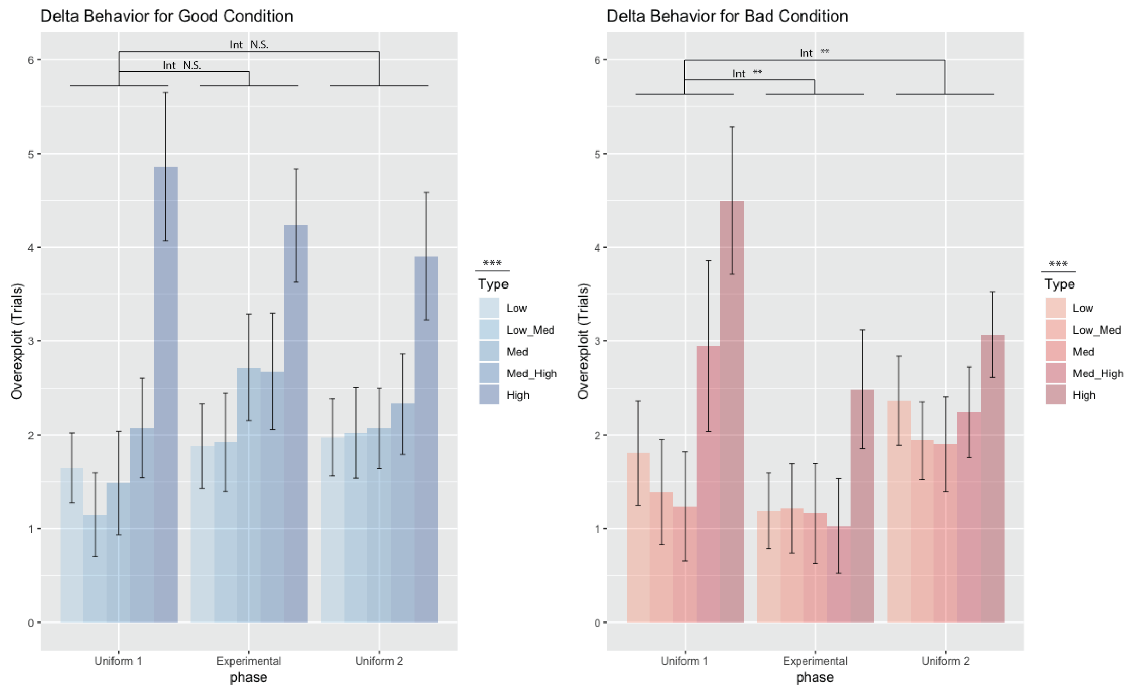


***Figure 7. Over-Exploitation of Partners by Player Type.*** *The effects of over-exploitation broken out by both phase and condition. Error bars denote +/- the standard error.*

**Table 4. People Over-Exploit Based on Cooperation Level of Partner**

$$Over - Exploitation_{i,t} = \beta_0 + \beta_1 Condition_{i,t} \times \beta_2 Player\ Type_{i,t} + \varepsilon$$

| Independent variable | Estimate (SE) | t | p |
|---|---|---|---|
| Intercept | 0.69 (0.40) | 1.71 | 0.909 |
| Bad Condition | -0.12 (0.58) | -0.21 | 0.836 |
| Player Type | 0.62 (0.09) | 6.89 | <.001*** |
| Bad Condition × Player Type | -0.11 (0.13) | -0.83 | 0.408 |

*Note.* Over-Exploitation ~ Condition × Player Type, where player type is a continuous variable defined as 1 being a low cooperation partner and 5 being a high cooperation partner. The good condition serves as the reference. Over-Exploitation is defined as number of trials beyond the optimal leave point. The model includes a random intercept and slope for player type for each subject.
* p < .05. ** p < .01. *** p <.001.

*Environments Influence Willingness to Cooperate with Good Partners:*

While the results have already examined the role of environment (Lenow et al. 2017; Frid, Burns, Baker, & Thorne, 2009) and social traits (Hackel et al., 2015) on foraging behavior independently, it is still unclear how changes in environmental quality might interact with the way people evaluate the importance of cooperation. In other words, it is possible that manipulations to the abundance or scarcity of an environment might cause players to undervalue and overvalue cooperation respectively.

To examine this question, we used a linear mixed effects regression to analyze the impact of condition (abundance/scarcity of cooperative players in an environment) and player type on decisions to over-exploit. If experiences in good and bad environments influenced social foraging then we would see a change in the partner's cooperativeness between the first uniform and good/bad environment. However, we found that environmental scarcity reduced subjects' willingness to over-exploit partners based on level of cooperation (see table 6) while environmental abundance had no effect on subjects' value of cooperation (see table 5). This showed that the scarce environment had a unique effect on the way subjects evaluated the cooperation level of partners. Specifically, in the first uniform environment subjects acted as if cooperativeness added value to the partnership but once they had experienced the bad environment subjects cared less about their partner's cooperativeness.

The same analysis was used to examine whether the effect caused by the bad environment also persisted into future foraging decisions. If the effects of the bad environment persisted into future foraging behavior then we would see changes in the way subjects evaluated cooperativeness between the first and second uniform environments. We found that the reduced willingness to over-exploit based on cooperation present in bad environments also carried over into the second uniform environment (see table 6). These results demonstrated how scarce environments altered the way subjects evaluated cooperativeness (as a social trait value) in both present and future social foraging decisions.

**Table 5. Degree of Over-Exploitation Changes Based on Player Type in Good Condition**

$$Over\ Exploitation_{i,t} = \beta_0 + \beta_1 Phase_{i,t} \times \beta_2 Player\ Type_{i,t} + \varepsilon$$

| Independent variable | Estimate (SE) | t | p |
|---|---|---|---|
| Intercept | 0.06 (0.57) | .105 | 0.917 |
| Phase (Good) | 1.11 (0.56) | 1.99 | 0.047* |
| Phase (Uniform #2) | 0.88 (0.53) | 1.66 | 0.097 |
| Player Type | 0.77 (0.11) | 6.92 | <.001*** |
| Phase (Good) × Player Type | -0.22 (0.16) | -1.34 | 0.182 |
| Phase (Uniform #2) × Player Type | -0.26 (0.16) | -1.67 | 0.094 |

*Note.* Over-Exploitation ~ Phase × Player Type, where Player Type is a continuous variable defined as 1 being a low cooperation partner and 5 being a high cooperation partner. The uniform #1 phase serves as the reference. Over-Exploitation is defined as number of trials beyond the optimal leave point. The model includes a random intercept and slope for player type for each subject.
* p < .05. ** p < .01. *** p <.001.

**Table 6. Value of Cooperation Reduced in Bad Environments**

$$Over - Exploitation_{i,t} = \beta_0 + \beta_1 Phase_{i,t} \times \beta_2 Player\ Type_{i,t} + \varepsilon$$

| Dependent variable | Estimate (SE) | t | p |
|---|---|---|---|
| Over-Exploitation | | | |
| Intercept | -0.1749 (0.61) | -0.29 | 0.775 |
| Phase (Bad) | 0.74 (0.57) | 1.30 | 0.193 |
| Phase (Uniform #2) | 1.51 (0.58) | 2.58 | 0.010* |
| Player Type | 0.86 (0.12) | 7.05 | <.001*** |
| Phase (Bad) × Player Type | -0.55 (0.17) | -3.23 | 0.001** |
| Phase (Uniform #2) × Player Type | -0.53 (0.17) | -3.07 | 0.002** |

*Note.* Over-Exploitation ~ Phase × Player Type, where Player Type is a continuous variable defined as 1 being a low cooperation partner and 5 being a high cooperation partner. The uniform #1 phase serves as the reference. Over-Exploitation is defined as number of trials beyond the optimal leave point. The model includes a random intercept and slope for player type for each subject.
* p < .05. ** p < .01. *** p <.001.

*Why do people over-exploit social partners?*

What might explain a person's overly exploitative behavior? One possibility is that the subject's suboptimal behavior was driven by an inaccurate choice rule. For example, based on our simulation, the optimal time to leave a partnership in a uniform environment was when the reward on a given round dips below 38.5 points. If a subject estimated a choice rule that determined they leave a partner when their reward dips below 20 points, they would naturally over-exploit partners beyond what was optimal. An inaccurate estimation of the optimal choice rule might bias towards exploiting a partner despite receiving suboptimal rewards. However, an alternative possibility is that subjects were inconsistently following their choice rule. This might manifest in subjects playing with some partners more than others when the optimal strategy was to leave a partner, regardless of the level of cooperation, once the reward dipped below their choice rule. Thus, a subject with a noisy, non-strict decision policy would have accidentally left when it was suboptimal, despite having the correct reward estimation.

To adjudicate between these two possible explanations for over-exploitation, we ran a logistic mixed effects regression model on subjects' choices to explore or exploit their partner as a function of the reward on a given trial. By fitting the distribution of subjects' decisions, we could extract two parameters: 1) a subject's intercept specifies the reward threshold that predicts an equal likelihood of exploring or exploiting (i.e., 50% indifference point), and 2) a subject's slope specifies how deterministic choices were made. For example, in Figure 8 the solid black line shows a high slope indicating there was less noise in a subject's choices.

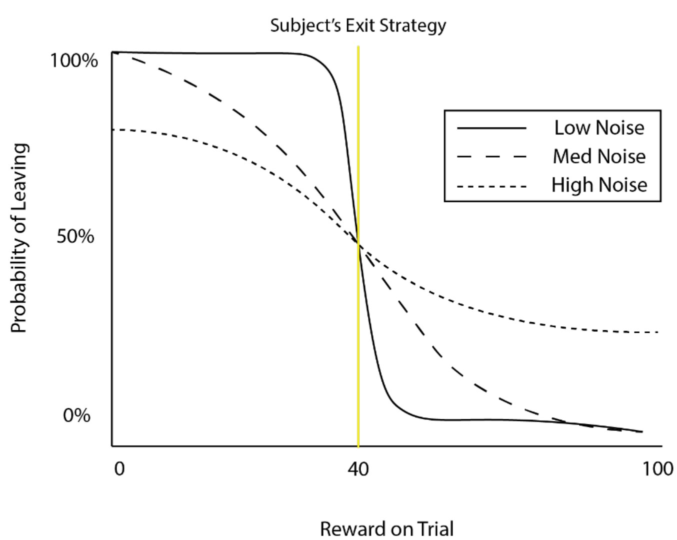


***Figure 8.*** *Example of multiple logistic choice rules of a hypothetical agent which demonstrate the noise component (how flat the sigmoid is) and choice rule estimate or exit strategy (inflection point of sigmoid indicated by the yellow vertical line).*

We used these subject-specific parameters (choice rule estimate and noise) to predict subject specific over-exploitation. The results from this analysis demonstrate that both the choice rule estimate (i.e., estimated reward threshold per subject) and noise (i.e., strength of subject's choice policy) independently contribute to over-exploitation. In other words, subjects with a higher reward threshold were less likely to over-exploit and subjects with more deterministic choice policies (i.e., less noisy) were also less likely to over-exploit. In addition, the interaction revealed that the combination of both factors was critical in biasing choice. Subjects who had both a high reward threshold and a strict choice policy performed the most optimally in our social foraging task.

**Table 7. Choice Rule Estimates and Noise Both Predict Over-Exploitation**

$$Over - Exploitation_{i,t} = \beta_0 + \beta_1 Slope_{i,t} \times \beta_2 Choice\ Rule\ Estimate_{i,t} + \varepsilon$$

| Independent Variable | Estimate (SE) | t | p |
|---|---|---|---|
| Intercept | -3.00 (0.43) | -6.96 | <.001*** |
| Noise | -43.15 (3.19) | -13.50 | <.001*** |
| Choice Rule Estimate | -1.56 (0.14) | -10.89 | <.001*** |
| Noise × Choice Rule Estimate | -1.79 (0.75) | -2.38 | .02* |

*Note.* Over-Exploitation ~ Slope × Choice Rule Estimate, where noise and choice rule estimate both had (0) as their reference category. Over-Exploitation is defined as number of trials beyond the optimal leave point that a subject stays for.
* p < .05.     ** p < .01.     *** p <.001.

## Discussion:

The purpose of this research was to investigate how people make social foraging decisions in different environments. Our results reveal that people tend to stay with partners longer than they optimally should have. This preference to overstay is further biased by the cooperativeness of the partners—independent of the reward received. Furthermore, the degree to which subjects cared about a partner's cooperativeness shifted depending on the quality of the environment. Specifically, people playing in scarce environments (i.e., where there are many uncooperative players) exploited partners less, and these choices were not biased by the partner's level of cooperation. Moreover, this bias to ignore the cooperativeness of partners continued to persist even after leaving uncooperative environments. Ultimately, we found that over-exploitation can be explained by participants underestimating the value of finding a new partner.

By departing from the traditional agricultural foraging paradigms used in past research (Charnov, 1976; Constantino & Daw, 2011; Lenow et al. 2017), our social foraging paradigm examined whether social traits like cooperation can influence a subject's ability to optimally decide. Evidence from a purely reward-maximizing account predicted that people would ignore social traits such as cooperation and focus purely on the monetary gains received. However, our results do not support this. First, subjects overwhelmingly over-exploited beyond what was optimal. Second, they adjusted their foraging behavior depending on their partner's cooperativeness. These findings demonstrate that an additional factor—in this case, social traits such as cooperation—governs whether a person will behave optimally (Rigdon, Ishii, Watabe, & Kitayama, 2009). While this account of cooperation does explain over-exploitation of highly cooperative partners, it does not explain over-exploitation of low cooperation partners. An alternative possibility is that the tendency to over-exploit in a social context could be driven by the psychology of sunk-costs (Roth, Robbert, & Straus, 2015). Research on sunk-costs demonstrates a difficulty to leave options that people had already committed time and resources to. Moreover, interpersonal sunk-costs—choice further weighted by the time and resources a partner has already committed (Olivola, 2018)—provide an account for over-exploitation of low cooperation partners.

To further examine the role of social traits, we investigated how environmental manipulations like scarcity (Lenow et al. 2017; Frid, Burns, Baker, & Thorne, 2009) influence social foraging. Results demonstrate that people over-exploited more in abundant environments, but less so when environments were scarce. These environmental manipulations influenced the perceived value of social traits in bad environments by lowering one's willingness to cooperate. This effect was so strong that it persisted in subsequent foraging contexts. One potential explanation for these lowered evaluations of cooperation may be due to habituation to inequality, which would induce subjects to leave earlier (Bicchieri & Chavez, 2010).

While I have provided some potential psychological reasons for why people over-exploit in social contexts, they do not detail a mechanism. That is because we observed that both accurate choice rule estimates and noisy behavior contributed to over-exploitation. In classic foraging tasks the MVT (Charnov, 1976) identifies accurate choice rule estimates of the optimal strategy as the critical variable leading to optimal foraging. However, we observed that unlike the MVT, the importance of choice consistency—or a subject's ability to stick with their choice rule—better explains over-exploitation. Given that we found that accurate choice rule estimates and noisy behavior contribute to over-exploitation, and that those who are more likely to over-exploit were also more likely to adjust their choice rule based on the type of player they were interacting with, suggests discrete mechanistic strategies contribute to social foraging. Future research that can provide a causal cognitive mechanism accounting for these distinct foraging strategies will be beneficial.

## Conclusion

This research gives insight into how people evaluate current social relationships, weighing up whether it is better to stay in the relationship or cut ties in favor of something potentially better. While past literature on foraging theory has documented that reward-maximizing frameworks such as the MVT and environmental influences such as scarcity bias agricultural foraging, it was not clear whether these findings would translate to social contexts.

This research fills this gap in knowledge by examining how social traits (the cooperativeness of a partner) and environmental quality (the number of highly cooperative partners) influence how people evaluate relationships. We found that people not only have a tendency to stay with partners longer than they reasonably should, but do so based on the cooperativeness of a person. This value of cooperation drastically changes depending on the environment in which partners meet. In environments with many cooperative partners, people tend to place more value on a partner's cooperativeness when making decisions. These shifts in evaluating partners also carries over into evaluating future relationships in different environments. Mechanistically, these findings of over-exploitation are driven by a persons' ability to treat each partner the same, irrespective of their level of cooperation, and importantly by a person's inability to accurately estimate the value of finding a new partner. Together, findings from this study reveal the necessary consideration of social traits and environmental quality in human social foraging.

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## Supplementary

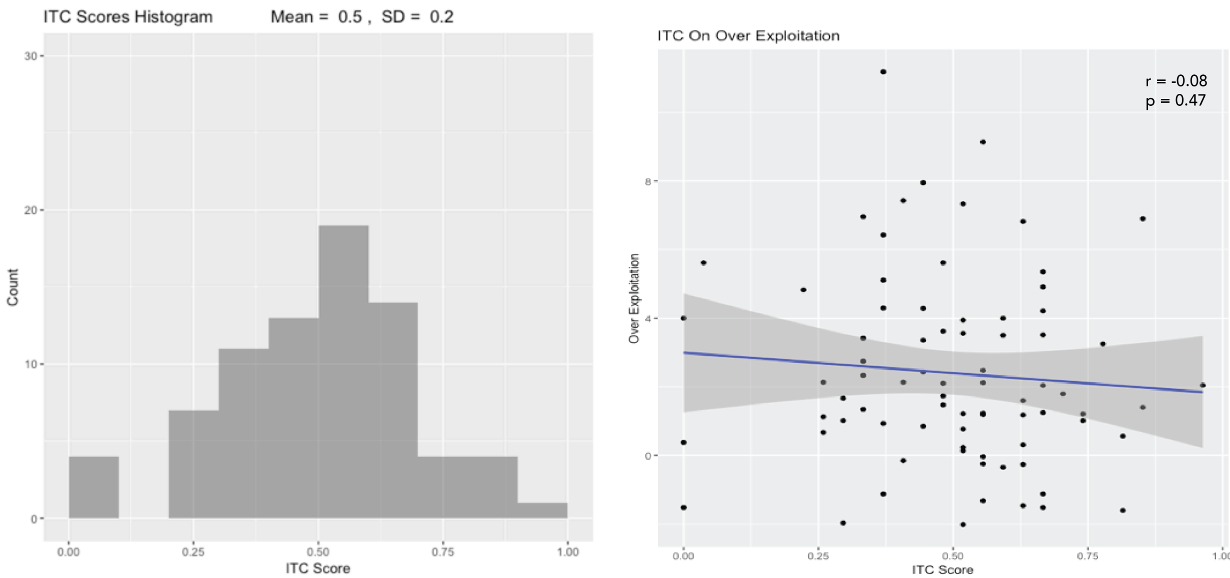
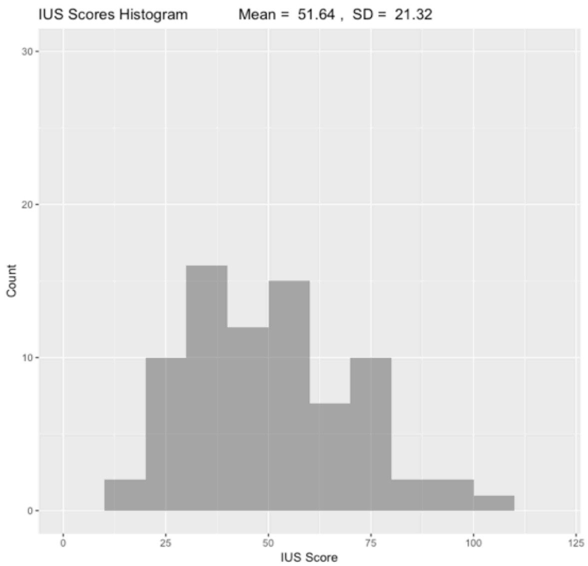



**Figure s1. ITC Score Distribution and Correlation**. *ITC scores measured from participants show a normal distribution of the scores and no correlation between the preference for immediate rewards and over-exploitation.*



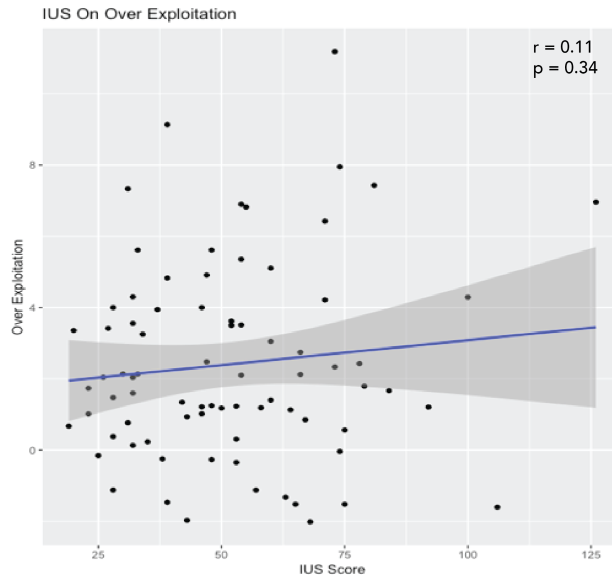




**Figure s2. IUS Score Distribution and Correlation**. *IUS scores measured from participants show a normal distribution of the scores and no correlation between intolerance to uncertainty and over-exploitation.*

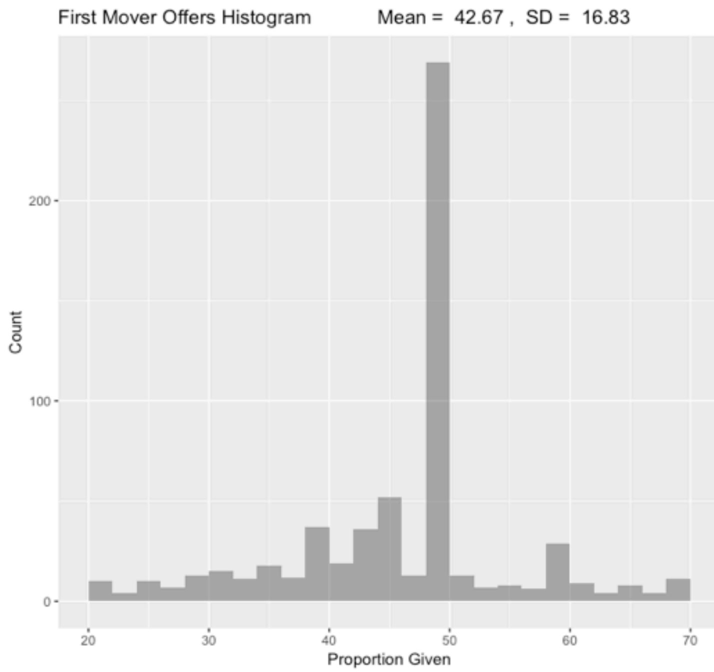



**Figure s3. First Mover Distribution.** *When subjects were asked to choose what proportion of the threshold they would like to give, they on average offered to give 42.67% of the threshold. This proportion is not significantly different from the 40% average cooperation level used in the uniform environment of our task.*

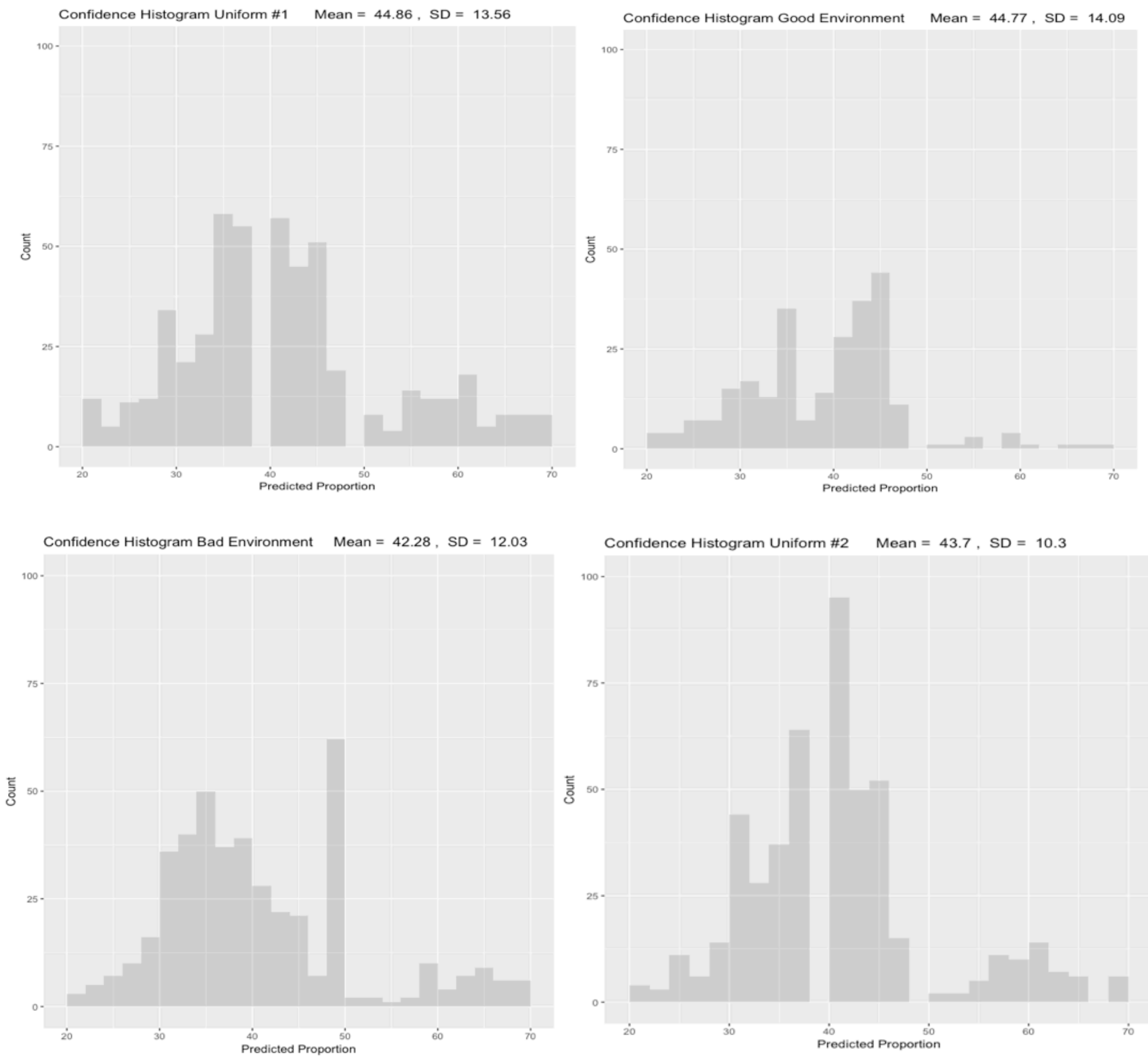



**Figure s4. Predicted Proportion Partner Would Give.** *Predicted cooperation level of partners collected weren't significantly different from the true average of each of the environments.*

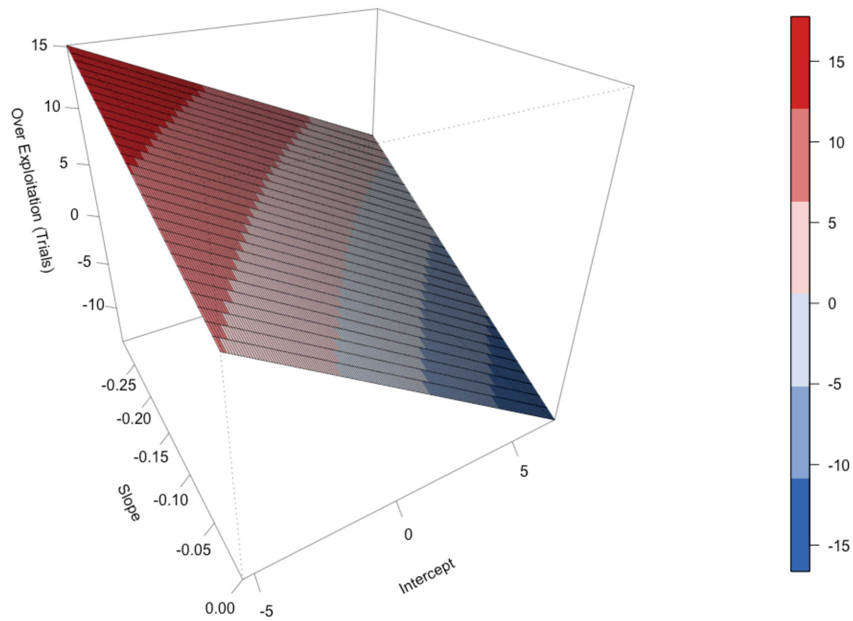



**Figure s5. Interaction Between Choice Rule Estimate (Intercept) and Noise (Slope)** *The interaction between slope (noise) and intercept (choice rule) in predicting over-exploitation can be seen in the curving of the intercept axes. The higher a subject's intercept, the higher their value of leaving and the more likely they are to under-exploit. The intercept is bounded between -5 and 5 so it does not reflect the exact point value of their choice rule but rather a scaled valued.*

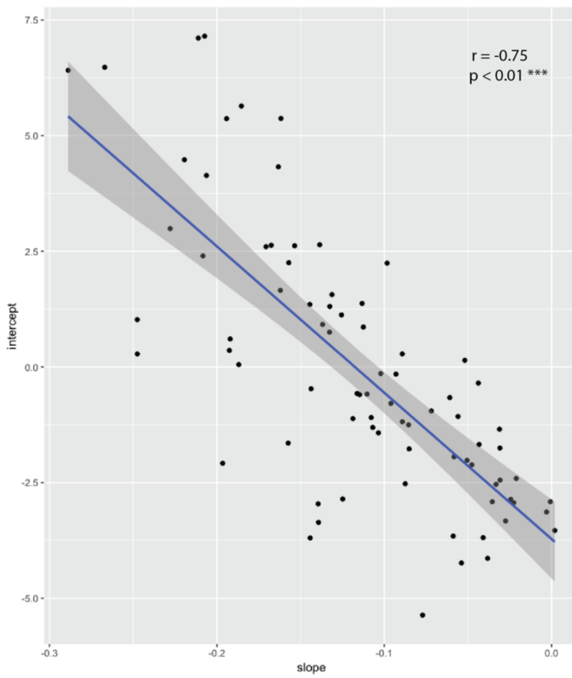



**Figure s6. Correlation Between Choice Rule Estimate (Intercept) and Noise (Slope)** *Correlation between intercept (choice rule) and slope (noise) reveals a correlation between people with high intercepts (leaving while the reward for staying is higher) and low slopes (more consistent leave points). This correlation suggests a link between a person's ability to estimate a reward-maximizing choice rule and how consistently they follow it.*