The Fair Side of Chance: How Uncertainty, Power and Fairness Impact Strategic Behavior

Jordan Selesnick (jselesni@sas.upenn.edu)

Andrew Cullen (atcullen@sas.upenn.edu)

Steven Jacobs (shjacobs@sas.upenn.edu)

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**ABSTRACT**

Uncertainty plays a fundamental role in contribution decisions for public goods. In public goods games (PGGs), researchers have explored the impact of two types of uncertainty on contribution rates: strategic uncertainty (ambiguity about other players' decisions) and to a lesser extent, resource uncertainty (ambiguity about the public good itself). In this paper, we explore how the way in which resource uncertainty is framed – particularly around perceptions of fairness – affects both contributions to a public good, and perceptions of fairness. We will use MTurk to conduct between-subject PGGs, randomizing participants into 5 conditions that vary how uncertainty is determined, and who it affects. Participants will read an uncertainty statement based on their condition and then play 8 rounds of a stranger PGG designed in Smartriqs. They will then be asked a series of questions aimed at understanding how fair they believe the game to be, and how large a role fairness played in their decisions. Wilcoxon rank sum tests will be used to measure differences between treatment arms relative to themselves and the control group.

**INTRODUCTION**

Throughout the discourse on prosocial behavior in public goods settings, uncertainty is a crucial factor that has been shown to influence decision making (Gangadharan & Nemes 2009). The most fundamental type of uncertainty is strategic: players cannot precisely determine what their partners will do. This leads to a challenge in coordination in which donations function as signaling tools that can potentially alleviate uncertainty. However imprecise, such signals lead to beliefs about others, which have been shown to impact decisions. If a player believes that their partner will conditionally cooperate, they are likely to donate a high amount in early rounds to induce their partner to follow suit in the future. Yet risk persists; there is no guarantee that they will reciprocate.

Uncertainty in PGGs can also come from the public good itself – what we will call “resource uncertainty." The return created by a public good may not be stable or easily measurable. It is quite possible that the benefit of reducing emissions to preserve the public good of clean air may change as air pollution levels change, meaning one’s action today may not provide the same benefit tomorrow. The proportion of benefits realized may change as well, when the gains of a public good become more favorable for certain groups. In the laboratory, these phenomena manifest themselves as the MPCR, and the proportion of the public fund that players receive.

Resource uncertainty is less studied than its strategic cousin, yet we believe it plays a critical factor in understanding how people interact with public goods. In the literature, there have been two crucial findings that have shed light on unique aspects of resource uncertainty. First, a series of papers by Dannenberg et al. use the threshold PGG model to explore the impact of introducing different levels of uncertainty in the “threshold” that determines when subjects receive payments. Here, the researchers found that individuals contribute less to public goods when thresholds are uncertain, presumably due to the risk that their contributions may lead to low payoffs if below the unclear threshold (Dannenberg et al. 2011). Second, Butera and List evaluated whether bounded uncertainty of the MPCR impacted contribution rates. They found that individuals gave more to the public good when the MPCR was uncertain with a high effect in their initial study, and a smaller effect in replications (Butera, List, & Villeval, 2020). The higher contributions were likely due to opacity; it was unclear to players whether outcomes were due to a variable MPCR or the contributions of their partners, a finding we discuss in more detail in our Theory of Change section (Butera & List, 2017).

While the aforementioned studies provide valuable insight into the role of resource uncertainty in PGGs, they do not address two key factors inherent to resource uncertainty that we believe potentially play a role in contribution decisions: power and parity. First, existing literature frames uncertainty primarily as a “fair” function of the game where all parties involved experience it equally (Gächter, Kölle, & Quercia, 2017). We believe that this does not accurately reflect experience with a public good, which though collectively owned is often managed by a group of individuals in power. Others may feel that uncertainty created by the managing group is less fair relative to a random cause, a factor likely to impact contribution decisions. Second, the studies mentioned each explore resource uncertainty as shared experience across all parties. However, individuals often do not experience the same level of uncertainty around a given public good. Certain individuals or groups are often insulated from effects of uncertainty. We believe imparity is an important social factor, which needs to be explored when evaluating the impact of uncertainty in PGGs. We aim to dissect these factors by isolating and controlling them in an effort to capture their effect in the context of a repeated PGG.

**Research questions:**

1. Does resource uncertainty (represented by the MPCR) alter the willingness of individuals to contribute to a public good.
2. Do beliefs about the source of the uncertainty (e.g. whether uncertainty is caused by individuals or is a function of nature) alter an individual's willingness to contribute to a public good.
3. Do beliefs about parity (e.g. whether certain individuals experience uncertainty and others do not) alter an individual's willingness to contribute to a public good.

**RESEARCH DESIGN**

**Basic Methodological Framework**

To complete our experimental research, we will employ a five-condition between-subject design with the aim of exploring the impact of subjects’ perceptions of the source (power) and information inequality (parity) on their willingness to contribute to public goods. This experiment will be conducted via an online Qualtrics survey from Amazon Mechanical Turk (MTurk). These participants will be randomly assigned to one of 5 conditions:

*(a)*  SystemicEqual

*(b)* SystemicUnequal

*(c)*  AgentEqual

*(d)*  AgentUnequal

*(e)* Control

The conditions will have the two of the following attributes (one from power, and one from parity):

**Parity**

Equal: Every individual will be given the same amount of information. They will not know the multipliers before they make their contributions.

Unequal: Participants will be randomly assigned to ‘favored’ or ‘unfavored’ sub condition.

1. Favored: will be shown the multipliers each round before making their contributions.
2. Unfavored: will not be shown the multipliers until after they make their contributions.

**Power**

Systemic: Participants are told that the multipliers were determined randomly.

Agent: Participants are told that the experimenters deliberately chose the multipliers.

Thus, our conditions will be Equal Systemic, Equal Agent, Unequal Systemic, and Unequal Agent.

**Hypotheses**

**Contributions in the experimental groups will differ from the control**

**H1:** Contribution rates for individuals in the Agent Equal condition will be significantly greater than those in control condition.

**H2:** Contribution rates for individuals in Agent Unequal will be significantly less than in the control.

**H3:** Contribution rates for individuals in Systemic Equal condition will be significantly greater than those in the control condition.

**H4:** Contribution rates for individuals in Systemic Unequal condition will be significantly less than those in the control condition.

**Contributions in the Agent Conditions the Equal conditions will be greater than in the Unequal conditions**

**H5:** Contribution rates for individuals in Equal conditions will be significantly greater than in Unequal conditions.

**H6:** Contribution rates for individuals in the Systemic condition will be significantly greater than those in the Agent condition.

**Fairness will impact contributions across conditions.**

**H7**: Fairness scores will be positively correlated with contribution rates across conditions.

**H8**: Participants in equal conditions will give higher fairness scores than those in unequal conditions.

**H9:** Systemic conditions will give higher fairness scores than in Agent conditions.

**Outcome Variable(s)**

Mean contribution rate over all trials. Fairness Likert scores.

**Intervention(s)**

Our experiment will be conducted on MTurk. Participants will be randomly assigned into one of X conditions: C1, C2, C3, C4, C5. Participants will be randomized using Qualtrics’ randomizer function. Participants will not be aware of any conditions other than the one they are in. Full instructions and materials can be found in Appendix A.

*Summary of instructions*

1. Consent statement
2. CAPTCHA Bot Check
3. Introduction to the experiment:
   1. Structure of game explained
   2. Incentivization / payout explained
4. Comprehension Check
5. Randomized into 1 of 5 conditions
6. Uncertainty statement (by condition, sans control)
   1. Agent
   2. Systemic
   3. Unequal
   4. Equal
7. Placed into Smartrics game play
   1. Play 8 rounds
   2. Play with the same partner each round
8. Fairness Elicitation
   1. Subjects respond to a series of questions centered around how fair they perceived the game to be, using Likert scales.
      1. Fairness questions.
      2. Uncertainty questions.
9. Demographic information
   1. Age
   2. Gender
   3. Race

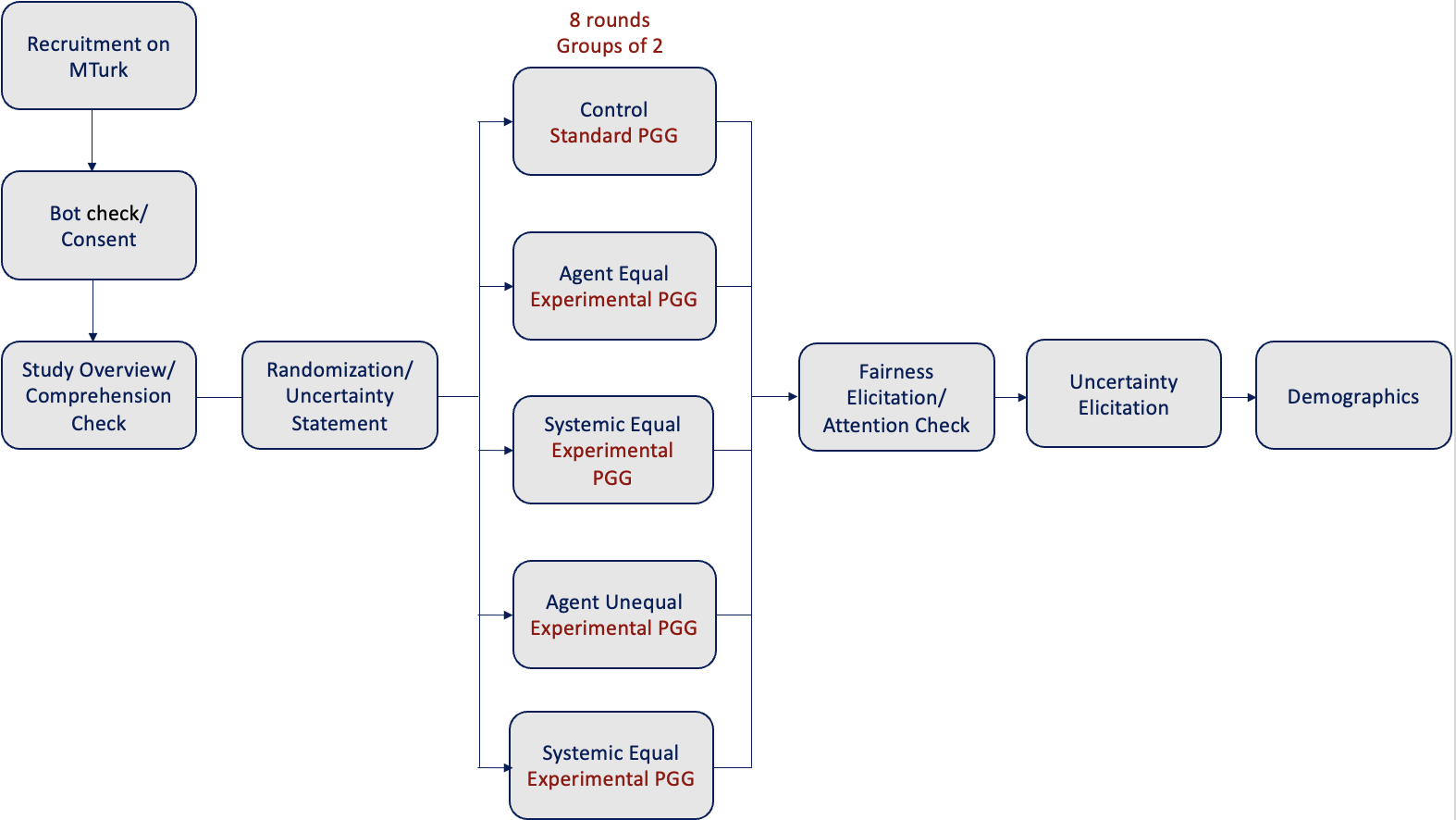


Figure 1: Overview of Experimental Design

**Theory of Change**

Uncertainty about the decisions of others is implicit in PGGs. The literature suggests that the less a subject knows about who the other players are, the less they contribute to a public good. Routinely, subjects in “stranger games” show lower contribution rates, presumably due to the absence of long term signaling incentives.

However, uncertainty in public goods decisions extends beyond individuals’ ability to predict each other’s behavior. Investments in common pool resources such as water infrastructure or climate management do not have a fixed return. Resource uncertainty – ambiguity around the marginal return on individual investments into a common pool – is an important, but understudied, part of the public goods literature.

The existing literature is less clear on the impact of resource uncertainty on public goods investment. Experiments on threshold PGGs found that uncertainty around the threshold at which a resource “pays out” leads to lower contributions from subjects. Adding to the belief that resource uncertainty reduces prosocial behavior, Dannenberg et al. showed that when individuals are less certain about the outcome of their donations, they tend to donate less. However, Resource Uncertainty does not always appear to have an antisocial impact. List shows that under certain circumstances, Knightian uncertainty could actually increase pro social behavior in a public good allocation game. This, List explains, is because institutional uncertainty extends into the debate of fairness. Typically in repeated PGGs, players ‘punish’ freeriders for their selfish behavior by lowering their contributions in later rounds. In the presence of institutional uncertainty the information is obscured; players are unable to distinguish between a low outcome due to opposing freeriders, and a low outcome due to a small MPCR. Therefore, many participants punished others less by contributing more.

Common pool resources might exist in nature, but in a social context they are typically managed. Building off of List’s work, we hypothesize that perceptions of fairness will confound existing findings about the impact of resource uncertainty on willingness to contribute to a public good due to strategic uncertainty. We are interested in examining the role of uncertainty in a new context by applying it to game rules. We believe that by controlling for perceptions of power (Agent and Systemic conditions) and parity (Equal and Unequal conditions) we will be able to show the negative interaction effect between social expectations and Knightian uncertainty.

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**Variations from the intended sample.**

Attrition is sometimes unavoidable, but with appropriate considerations its impact can be mitigated. A standard rule of thumb is that less than 5% attrition introduces negligible bias, whereas more than 20% attrition poses major threats to experimental validity (Schulz & Grimes, 2002). Based on pretest results we expect an attrition rate of 15% in the final experiment. For this reason, we aim to keep attrition rates as low as possible and propose several solutions for doing so.

Any failure to complete the task or other forms of non-compliance with the condition will result in a participant’s exclusion from analyses. Our study is designed so that participants will not be eligible for the Amazon gift card lottery unless they have completed the study in its entirety. This endogenous incentive is coupled with the exogenous incentive of participants’ MTurk profiles being scored lower upon failure to complete a Human Intelligence Task (HIT). Finally, the inherent brevity and simplicity of our task, along with its fair pay will likely not induce attrition or discourage participation in any way.

**DATA COLLECTION AND PROCESSING**

In line with previous research informing this study, formal data collection will be conducted using MTurk, and, thus, the majority of respondents are expected to be U.S. residents. The composition of MTurk participants is also likely to be more diverse and more representative of the U.S. population, with only minor deviations, than sample pools of studies run exclusively on college campuses (Crump et. al., 2013).

**Types of Data**

We plan to collect the following types of data:

| **Data Element** | **Text Prompt** | **Data Type (Variable)** |
| --- | --- | --- |
| Consent | “By clicking the arrow at the bottom of this page you are giving your consent to participate. You are also verifying that you are at least 18 years of age. “ | “Clicked arrow.”  “Exited page.” (categorical) |
| Bot Check | CAPTCHA check. | Completed check (categorical) |
| Comprehension Check #1 | “What happens to the sum of tokens contributed to the public account?” | “It is multiplied by the multiplier, and then divided based on who contributed most.” “It is multiplied by the multiplier, and then divided evenly to all participants.” “It is expropriated by the experimenters.” “20 more tokens are added to it, and then it is divided evenly to all participants.” (categorical) |
| Comprehension Check #2 | “How are the multipliers determined?” | “Deliberately chosen by the experimenters” “Randomly selected by a computer” “Not chosen” (categorical) (correct answer depends on condition) |
| Contribution (repeated for each round) | “Please indicate in the box below how many tokens to transfer to the public account.” | Entered by subject (ordinal between 1 -20) |
| Fairness #1 | “Did you feel that the rules of the game were fair?” | -5 to 5 Likert scale  (ordinal) |
| Fairness #2 | “My perception of fairness affected my contribution decision.” | -5 to 5 Likert scale  (ordinal) |
| Fairness #3 | “How the multiplier was determined (intentionally vs. randomly decided) was important for how fair I perceived the game to be.” | -5 to 5 Likert scale  (ordinal) |
| Attention Check #2 | “Please select the largest even number listed below.” | -5 to 5 scale  (ordinal) |
| Uncertainty #1 | “How uncertain did you feel about the value of the multipliers?” | -5 to 5 Likert scale  (ordinal) |
| Uncertainty #2 | “How uncertain did you feel about what your partner would contribute?” | -5 to 5 Likert scale (ordinal) |
| Uncertainty #3 | “How important was the multiplier in your contribution decisions?” | -5 to 5 Likert scale (ordinal) |
| Uncertainty #4 | “How important was your partner's behavior in your contribution decisions?” | -5 to 5 Likert scale (ordinal) |
| Self-reported demographics, age | “How old are you?” | Age, in years  (ordinal) |
| Self-reported demographics, gender | “Please indicate your gender.” | “Male”  “Female”  “Other/would rather not disclose”  (categorical) |
| Self-reported demographics, ethnicity | “What is your race/ethnicity?” | “Asian/Pacific Islander” “White” “Black/African American” “Native American” “Hispanic/Latino” “Not Listed” (categorical) |
| Comments | “If you have any comments that you would like to leave, you may do so below.” | Text entry. |

**Sample**

For our experiment, the participants and subsequent data will be recruited and obtained exclusively through MTurk. We determined that at a significance level of α = .05 and effect size of d = 0.215 (the average of effect sizes from Butera et al. (2020) [.42] and our pretest [.09], we ran an *a priori* sample size calculation indicating that 2142 subjects (428 per condition) would be required to detect effects with 80% power. However, we will be limited to a budget of $1,000 for this experiment. $100 was used to conduct the pretest and $200 will be used to pay for Amazon Gift Cards, leaving with us with $700 for show up fees. Given the 40% Mturk fee, we will be able to collect 1,000 observations total, leaving us underpowered given our analysis.

**Collection Method, Data Sources, and Timeline**

Data for this study will be collected using MTurk. Pretest data will be collected on 04/07/2022 using $100 of the allocated research funds to find any errors in survey design. Formal data collection will occur on 04/13/2022.

**Termination considerations and stopping rule**

Data collection will be terminated upon spending $500 of the researchers funds to pay show up fees for Mturkers. Observations will be excluded from analysis on the basis of any of the following conditions:

1. Observation durations longer than 45 minutes
2. Failing to complete all elements of the experiment
3. Failing the bot check
4. Failing the attention check
5. Getting matched with a bot in the lobby of the of the PGG rather than another player

**Data management plan**

*Tools*

The experiment survey will be created using Qualtrics with a modified Repeated Partner PGG template from Smartriqs. Analysis will primarily be conducted using R Studio. Some preliminary data cleaning and analysis may be conducted using Microsoft Excel on an as-needed basis. To collect the final data, participants will be solicited to complete the experiment via MTurk.

*Confidentiality*

The research team will ensure and strictly maintain confidentiality. Each participant’s responses and data will be assigned a random ID number to preserve anonymity. Participant data will not be accessible to anyone outside the research team and their advisors. Consent for participation will be requested. Individual responses will be reported as aggregate data. At no point will individual responses be reported in isolation as to be made identifiable. Although demographic information will be collected, no personal or otherwise sensitive information will be requested or stored. Subjects may omit responses to demographic questions, and they will retain the right to withdraw from the experiment at any time, at which point their data will be destroyed.

*Storage*

Subject responses will be collected and stored as a .sav file on a password-protected computer only accessible by authorized researchers and their advisors. Confidential data will be destroyed seven years after the data collection period has ended.

**Pilot Data Collection**

On 03/22/2022, the research team will begin contacting individuals within their respective social networks to collect preliminary data for the experiment with the intention of reaching 40 total observations. This will help identify any problems with the experiment before a subsequent MTurk pretest. Methods of solicitation include, but are not limited to, sharing the survey on Facebook, Twitter, other social media platforms, privately messaging family members, and posting survey links within Slack workgroups. Pilot-phase participants will be asked the full set of standard experiment questions.

Following the initial pretest, the research team will run a pretest on MTurk, the platform which will host the final experiment on 04/04/2022. This will further identify potential problems with the participant’s experience of the experiment before performing the final data collection. Again, this cohort of participants will be asked the full set of standard experiment questions.

**Final** **Data Collection**

Beginning 04/13/2022 the research team will run our Qualtrics survey on Mturk and begin collecting data. The final sample size will be approximately 1400 participants before exclusions.

**Compensation structure**

Each participant will be paid a show up fee in line with the approximate hourly wage of Mturk workers. The study will be made incentive compatible by entering each participant into a lottery for one of 8 $50 Amazon gift cards. Performance will be incentivized by weighting lottery selection based on the amount of tokens the participant finishes the game with (final payout). The lottery will be conducted after the final data collection has been completed and winners will be contacted on Mturk and given their gift cards.

**EMPIRICAL ANALYSIS**

**Statistical Methods**

*Main evaluation and underlying assumptions*

Because we have a limited amount of funds to compensate participants, our sample size will end up being smaller than preferred. This will impact the effectiveness of parametric tests because the assumptions of normality and homogeneity of variances may not be met. The assumption of independence between observations will be met though, given our between-subject design. We will conduct a Wilcoxon Rank Sum test to measure our primary research questions. We will also conduct a regression model to test the robustness of our effects as well as the effects of fairness and uncertainty on contributions. These tests will allow us to circumvent issues of non-normality, heterogeneity of variances, and floor and ceiling effects.

*Rules for missing values*

To try to mitigate issues of missing values, the Qualtrics design will require participants to complete the questions on each page before moving forward. If, though, missing values do arise for any other reason, those participants will be excluded from the analysis.

**Statistical Model**

*Main statistical tests*

For all six of our hypotheses, we will conduct the non-parametric Wilcoxon Rank-Sum Test because of the limits in sample size and the difficulties of assuming normality of our distribution as well as heterogeneity of variances. With these tests, we will compare each condition to the control (**H1-H4**) as well as the interaction between experimental conditions to each other **(H5 & H6**).

**Regression model**

We will design an ordinary least squares (OLS) regression model to test the effect of fairness of our results (**H7 & H8**). An OLS will also allow us to control for floor and ceiling effects in our data. We acknowledge that this will introduce some bias into our results that could be mitigated by using a Tobit regression (Mcbee, 2010). However, these tests assume floor effects are a result of nonparticipation (Foster & Kalenkoski, 2013). Though, in PGGs not contributing is a viable strategy and does not indicate nonparticipation. This regression will assist us in controlling for any possible effects caused by these variables. The model will be the following:

D = β0 + β1X1 + β2X2 + β3X3 + β4X4 + β5X5 + β6X6 + Ɛ

D = Dependent measures (Contribution rates)

β0 = Coefficient intercept

β1 - β6 = Coefficient estimates

X1 = Experimental group

X2 = Contribution Rates

X3 = Fairness #1

X4 = Fairness #2

X6 = Fairness #3

Ɛ = Error term

The Experimental group variable will be categorical and will correspond to each of the experimental groups. All of the other variables will be numerical data.

We will run another regression to test the robustness of our results. Specifically, we want to determine whether any demographic variables will impact the results seen in our dependent measures. The model will be the following:

D = β0 + β1X1 + β2X2 + β3X3 + β4X4 + β5X5 + β6X6 + Ɛ

D = Dependent measures (Contribution rates)

β0 = Coefficient intercept

β1 - β6 = Coefficient estimates

X1 = Experimental group

X2 = Contribution Rates

X3 = Age

X4 = Gender

X6 = Ethnicity

Ɛ = Error term

Age is a ratio variable that we will ask participants to enter in the survey manually. Only whole numbers will be allowed in the text box. Gender is a categorical variable that we will ask participants to choose from a list. The options will be Male, Female, Other. Ethnicity will also be a categorical variable.

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