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Ambigious settings in a linear public goods game

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Abstract

This study researched the effects of adding ambiguity to the public goods game. An online survey was conducted to examine the choices made in a simulated game. Significant evidence was found that incomplete information has a positive effect on average contribution. Statistical analysis was conducted on other possible influential factors, such as norm compliance and anchoring and adjustment. There was no evidence that these factors affected the results in any significant matter. The findings of this paper can be seen as a gateway to more research into the effect of an ambigious environment in a voluntary contribution mechanism. Potential further research is discussed as the degree of ambiguity aversion remains inconclusive.

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1 Introduction

Donating to charity has always been seen as a noble and altruistic action. It allows an individual to give to those in need, without creating the expectation of wanting something in return. As altruistic as this may sound, research has shown that this intrinsic incentive is not the only reason that charitable donations occur. This is illustrated by the fact that only around 5 percent of donations are anonymous (LiveScience, 2014). As a possible explanation for this Andreoni (1989, 1990) states that people may gain utility from the act of giving. This introduces the possibility that they showcase altruistic behaviour for self-righteous goals. There are also many charities that publicize the donations they receive in categories, as many donors tend to give the minimum amount necessary to get into such a category (Harbaugh, 1997). This shows that the donations happen due to the fact that donors gain utility from both their own approval (Andreoni, 1989; 1990) and the improved societal image (Holländer, 1990; Vesterlund, 2003).

Field experiments have been used extensively to research standard public goods experiments that use the Voluntary Contribution Mechanism (Isaac, Walker, & Williams, 1994; Chen, Li, & Mackie-Mason, 2006; Zarghamee et al., 2017; Pereda et al., 2019). This mechanism is commonly used to analyze decision making in public good allocation. VCM in its simplest form is based around giving participants a certain endowment and letting them decide how much of this endowment they wish to contribute towards a public goods fund (EconPort, 2006). VCM applies to both charitable organizations and to some extent the allocation of public goods within a nation. The public goods game is a well-documented experiment, in which participants start with an equal amount of initial wealth and have to decide each round how much of their wealth they wish to add to the common pool. This illustrates the simple form of a VCM. The researchers will then multiply the amount that is in the common pool by a certain factor and redistribute the multiplied amount equally over all participants. The amount that the contestants do not add to the fund will be send to their personal wallet.

The social optimum level is acquired when everyone allocates all their money to the common pool every single round, as that scenario allows all initial wealth to be multiplied. This is a societal Pareto efficiency level, as no player can acquire a higher payout without hurting others (Hokamp & Pickhardt, 2011). On an individual level, allocation of all endowment to the personal wallet allows for the highest payout. This constitutes to a Nash-equilibrium in which no participant contributes to the common pool (Saijo &Yamato, 1999). These interdimensional differences illustrate the problems at hand, as every participant has to weigh these options against their own behavior whilst contemplating what the other participants' preferences might be.

Although the public goods game has been researched extensively, many findings show different patterns at individual level. Kurzban and Houser (2001) were able to categorize three types of participants. They classified players into being either strong cooperators, strong free riders or conditional cooperators of reciprocators. Previous studies have shown that contributions in iterated public goods games decrease over the course of the experiment. Average contribution starts between 40 to 60 percent, but it decays as more rounds are played (Ledyard & Palfrey, 1995; Zelmer 2003; Cox & Sadiraj 2007). Houser and Kurzban (2002) state that this decay may be caused by noise, such as errors or confusion, and participants choose differently in later stages of the experiment because they learn from their initial mistakes. These findings are partly based around the idea that participants change their decisions because of the actions of other participants. But if participants are uncertain what amount other contestants added to the common pool, then individual valuations such as norm compliance (Reuben & Riedl, 2013) and reciprocity (Barsley & Sausgruber, 2005; Croson, Fatas & Neugebauer, 2005) become neglectable. This could result in participants choosing options that more closely resemble their actual preferences and base their decisions on intrinsic value.

Ambiguity aversion is an anomaly that shows the humans' general preference for known risks over unknown risks. The aversion was popularised through the Ellsberg Paradox (Ellsberg, 1961). Ambiguity-averse people will overestimate the unknown probability of a certain risk and settle for an alternative preference with known probabilities. Easley and O'Hara (2009) concluded that some traders rationally choose to not participate in a market to avoid ambiguity. This aversion could also impact the choices of participants in the public goods game, as the preferences of others is unknown. They could decide to not add any of their endowment to the common pool in order to shield themselves from the event with unknown probability that no other participant adds anything to the common pool. The flip side of the coin is also possible, as participants could be reluctant to keep all their initial wealth to themselves. They could be afraid, consciously or unconsciously, of the event that every other participant shows strong cooperation in the first round. Humans in general are cooperative organisms (The Conversation, 2020), and therefore they might adjust their first round preferences to the chance that such an event might happen.

Brookshire, Coursey and Redington (1993) conducted an analysis on the effects of heterogeneity and information in a linear payout environment. In this linear setting, the amount that is added to the common pool gets multiplied by a constant value. This allows a linear payout in which participants receive an equal constant value for every dollar added. They found that incomplete information had a positive effect on contribution whilst heterogeneity had a negative effect on the average contribution. Chan, Mestelman, Moir & Muller (1999) concluded the contrary, as they found a negative effect on the contribution to the public goods game when less information was distributed. This effect was researched in a non-linear payout setting with three participants. Dannenberg, Löschel, Paolacci, Reif & Tavoni (2015) also found negative effects on contribution when ambiguity was added to threshold public goods game, by removing knowledge of the value of the threshold. However, ambiguity on its own has not been researched in a linear payout environment. In these settings it has only been researched in combination with other factors. This research is also very limited, with just a few studies that truly remove all information. Additionally, most of these studies consisted of public goods games with up to six participants (Chan et al., 1999; Kurzban & Houser, 2001; Dannenberg et al., 2015; Marini, García-Gallego & Corazzini, 2020). Isaac et al. (1994) stated that group size has a significant effect on the level of cooperation. It is uncertain what the effect would be when less information is distributed over larger groups. This is important information though, as many VCMs in real life are based on structures with countless participants. Because of this, the question this paper seeks to answer is:

Does a higher level of ambiguity significantly increase the level of cooperation shown in a linear public goods game?

Answering this research question opens the door to more research about the effect of ambiguity aversion in VCMs. The question is one-sided, because the expectation is that the mean contribution will be higher when less information is shared. This expectation is based on the findings from Brookshire et al. (1993). This research question will be answered with the use of an online survey where subjects participate in a simulated public goods experiment. Ambiguity aversion will be created by removing certain information that was shared with the participants in previous studies.

The scientific contribution of this paper is that it applies ambiguity aversion to the public goods game. It could show that participants might base their preferences on ambiguity aversion in VCMs. More practically, VCM is a structure that is used in most of the charitable organizations and also somewhat in the provision of public goods. The practical implications that could surface because of this paper could aid those structures and increase their revenue. If these organizations can better understand what influences the individuals that participate in their VCM, then this could optimize the analysis of all possible interventions.

Following this introduction there will first be a summary of the public goods game and ambiguity aversion. After this theoretical introduction, the methods used to answer the hypothesis and research question will be thoroughly explained. This section is dedicated to completely understand the structure of the experiment and to understand how the corresponding findings will be used for statistical analysis. This analysis will be next section in the paper. Lastly, conclusions about the hypothesis and research question will be made. The internal and external validity shall be discussed in the last section, along with practical implications and research possibilities for further studies.

2 Theory

2.1 Public Goods Game

The public goods game is one of the main games of experimental economics. It is based around the voluntary contribution mechanism (VCM). Initially the game was played over a single round, but in later versions more rounds were introduced. This is known as the iterated public goods game. Every participant, denoted $i \in \mathbb{N}$, receives an initial endowment ($x_0 \in \mathbb{N}$) and is required to choose the allocation of their wealth. They can choose to put any amount in their personal wallet ($z_i \in \mathbb{R}$) or a common pool ($w_i \in \mathbb{R}$). The total quantity of the common pool is given by the formula:

$$W_r = \sum_{i=1}^{N} w_i \tag{1}$$

W_r represents the total amount of wealth added to the common pool in a certain round. w_i respresents the contribution of participant i to the common pool with $w_i \in \mathbb{R}$. $N \in \mathbb{N}$ equals the total amount of participants. The researchers will multiply W by a certain factor. This multiplied amount will then be distributed equally over all contestants. This is represented by the marginal per capita return (*MPCR*; Isaac & Walker, 1988). In order to solidify a Prisoner's Dillema, the following assumption must hold: $N < MPCR < 1$. If this assumption holds then it means that a participant is worse off individually if he contributes to the common pool, but on a social level the sum of payouts does increase if an individual decides to add funds to the pool. In a linear payout environment, the marginal payout function is:

$$MPCR = \frac{\alpha}{N} \tag{2}$$

Constant $\alpha \in \mathbb{R}$ respresents the multiplier that the researchers use to increase the value of the common pool. Note that *MPCR* is a constant value because of the linear payout structure. Every round the participant chooses what to do with their current wealth, and these decisions are based on the following function:

$$X_{i,r} = MPCR * W_{r-1} = w_{i,r} + z_{i,r} \tag{3}$$

$X_{i,r} \in \mathbb{R}$ represents the budget constraint of individual *i* in round $r \in \mathbb{N}$. $w_{i,r} \in \mathbb{R}$ equals the allocated amount to the common pool by individual *i* in round *r*. $z_{i,r} \in \mathbb{R}$ represents the amount of money that individual *i* adds to their personal wallet in round *r*. These are the only two options for each individual, and therefore represent the total amount of wealth that was initially given to the participant in that round. This amount equals the quantity of the common pool from last round ($W_{r-1} \in \mathbb{R}$) multiplied by *MPCR*. The amount allocated to the personal wallet ($z_{i,r}$) will be a direct payout for the participant, and therefore the total payout for individual *i* after all rounds will be:

$$y_i = MPCR * W_{10} + \sum_{i=1}^{r} z_{i,r} \tag{4}$$

This equation shows that the payout is equal to the sum of the funds added to the personal wallet combined with the individual payout of the common pool in the last round of the experiment.

2.2 Pareto optimality

Pareto effiency is acquired in a certain game state when no individual can realise additional gains without disadvantaging others. Scoping in on the public goods game, many Pareto optimal game states can be acquired in each set of game rules. Although the most notable Pareto efficient allocation might be the game state in which every individual contributes the maximum amount to the common pool, every individual deviation from this allocation allows the possibility for another Pareto efficient game state. Hokamp and Pickhardt (2011) were able to mathmatically prove all possible pareto optimal allocations in typical public goods games. To prove that it was applicable on real datasets they analysed published public goods games. They showed that there are many Pareto optimal allocations, but most of these are strictly dominated by other allocations. These dominated game states were less likely to happen when certain factors were added, such as more information to the participants or a leadership role within the public goods game.

2.3 Nash-equilibrium

In a game state, if there is no agent that can change their strategy to increase their own expected payoff then this state is seen as a Nash equilibrium. The Nash equilibrium of the public goods game is for every individual to contribute nothing to the common pool (Saijo & Yamato, 1999). These choices are visible in a participant with an utility function that is based on maximizing their own payout:

$$U_i(y_i|NC) = \alpha^\beta y_i \tag{5}$$

In this function *NC* stands for none contributor, as money will only be allocated to the personal wallet. Variables α and β show the utility valuation, that is different for each individual. The only dependent factor of the experiment here is the payout of the individual himself, without any regard for any other participant. Therefore a *NC* would not contribute anything to the common pool, as the individual would decrease its expected payout and thus expected utility. In every other possible game state the individual's expected payout can be increased by contributing less to the public fund, and therefore in theory no contributions should be made. This zero contribution equilibrium only exists if the following assumption holds: $N < MPCR < 1$. If the *MPCR* is above 1 then this would imply that the multiplication factor is larger than the number of participants (*N*). In this case the Nash-equilibrium would be to contribute everything to the common pool.

2.4 Ambiguity aversion

Ambiguity aversion shows the humans' general preference for risks with known probability over those with unknown probability. Ambiguity-averse people overestimate the unknown probability of a certain risk and prefer to settle for an alternative preference with known probabilities. This aversion has been popularised by the Ellsberg experiment (Ellsberg, 1961) and since then it has been proven to be an anomaly. The definition of an anomaly is a robust and systematic empirical finding that contradicts an economic assumption or theory. Systematic findings imply that the results are not random, instead showing a deviation of behaviour in one direction. Easley and O'Hara (2009) were able to conclude that this aversion is also noticeable in finance, stating that nonparticipation arises by some traders to avoid ambiguity. There has been little to no studies conducted on the impact of ambiguity aversion in the public goods game. Although the aversion has been proven to exist, the limited research in this field of study does not allow any practical implications to be made of its influence on VCMs. The hypothesis that will be answered is:

Adding uncertainty to outcomes of a public goods game significantly increases the mean contribution.

This hypothesis will showcase in what direction ambiguity guides individual preference. Research has shown that participants of public goods game have a tendency to choose for a cooperative attitude, as Cone and Rand (2014) have shown by adding time pressure to the experiment. They suggested that the intuition of individuals favors cooperation over norm compliance. This more closely follows the intrinsic value of participants, which is also researched in this paper. Brookshire et al. (1993) found that incomplete information had a positive effect on the average contribution in a linear environment. On the other hand, ambiguity added by Chan et al. (1999) showed a decrease in cooperation. What should be noted is that their study did not follow the standard public goods game that is based on a linear payout. Because the experiment used in this study is based on a linear payout environment, incomplete information is expected to have a positive effect.

3 Methodology

3.1 Survey setup

To test the hypotheses and the research question, an online survey will be conducted in which a simulated environment of the public goods game is created. The answers of the participants will be compared to the average contribution level of the dataset from Isaac et al. (1994). They studied the correlation between group sizes and average contribution among students. Their sample of a single session, dollar payout system based on the voluntary contribution mechanism (VCM-SS-$ dataset) fits into the requirements of this experiment. The data was acquired from a group of 10 participants over a 10-period iterated public goods game. The online survey used will consist of the same game rules. An independent measures design will be used by randomly allocating participants to a treatment group and a control group. Cone and Rand (2014) found that experience with previous economic experiments has significant effect on preferences.. The design of the survey should account for these findings to avoid practice or experience effects. This will be done by randomly assigning individuals to a treatment group or control group. Subjects that participates in the treatment group can not also participate in the control group and vice versa.

The survey is split into two parts. The participants will first be asked several individual characteristics to establish the control variables. In these questions they will be asked their current occupation, as the only requirement for this study is that the participant is eligible only when he/she is a student. Other control variables include age, gender, ethnicity, political orientation and household income growing up (Cherry, Kroll & Shogren, 2005; Buckley & Croson, 2006). This also allows the opportunity to use the findings of this paper in the inconclusive discussions on the correlation between these control variables and the cooperation level. Gender is most notable in this category, as evidence on the effect of sex on cooperativeness in groups remain mixed. There were some studies that concluded insignificant differences (Caldwell, 1976; McClintock & Liebrand, 1988; Yamagishi, 1986). Contradicting significant results were also found, as Sell and Wilson (1991) found males to be more cooperative while Seguino, Stevens and Lutz (1996) found females to be more cooperative. Household income growing up also seems to be a necessary variable to evaluate as this showcases a certain standard of living. The concept of diminishing marginal utility of income and wealth is popularised by Alfred Marshall (1890) and it suggests that as income increases, the gain in satisfaction and happiness resulting from a fixed increase in wealth becomes smaller. This could imply that if students are raised in a household with a high income, they might value an increase in wealth from the experiment less than a student that was raised in a lower income household. Current income will not be used as the survey is aimed only at students.

The simulated public goods game will be conducted in the second half of the survey. First there will be clear instructions on the entire public goods game. Participants are told that they are assigned to a group of nine other imaginary participants and that the multiplication factor equals three. These game rules are all equal to the rules of the study from Isaac et al. (1994). The equation that was discussed prior thus shows:

$$MPCR = \frac{\alpha}{N} = \frac{3}{10} \tag{6}$$

MPCR represents the marginal per capita return, α equals the multiplication factor and N is the amount of participants in the public goods game. In order for there to be a prisoner's dilemma, the following assumption ($N < MPCR < 1$) must hold. In this study the assumption holds, and therefore a standard public goods game is realised. The participants are informed that no monetary incentive can be given due to limited resources. However, they are asked to participate in the experiment as if they would gain the sum allocated to the personal wallet. Although this is nowhere near perfect, it does allow for somewhat honest answers as participants understand everything surrounding the experiment.

Participants are then randomly allocated to either the control group or the treatment group. This allocation is executed by evenly distributing the individuals over each group through the randomization option of Qualtrics, as this also removes any possible bias from the researcher. The control group participates in a standard iterated public goods game where the agents will be informed of the average contribution level (from the results of the previous study) each round. The treatment group will not know the average contribution each round, instead they will only receive information whether their answer is higher, equal or below the mean value.[1]

3.2 Analytical methods

The mean contribution levels that were shared in the online survey were gathered from the dataset of Isaac et al. (1994). In the control group these average values were shared with the participants after the round, whilst the treatment group only received knowledge of whether they were above or below this value. It is uncertain if the assumptions of parametric tests hold in this online survey. A full analysis of these assumptions will be conducted first. If the data allows the use of parametric tests, then the process of conducting these tests will be further explained in the analysis section of the paper.

[1] There was an error in the randomization process of the online survey. This forced the subjects to participate in the experiment in both the treatment group and the control group, thus participating in two public goods games. Randomization only occurred in what group the subjects started. Rand et al. (2014) found that experience in economic field experiments has a significant effect on subjects' preferences. For that reason, only the first experiment from each subject will be used in this analysis to prevent this experience effect from influencing the dataset. Therefore a between-subject analyses will be conducted, instead of a within-subject analysis that would compare the answers from both experiments per individual.

The first hypothesis stated that average contribution will decrease when less information is shared. This can be researched by comparing the average contribution of the treatment group with the average contribution of the control group. This analysis will be performed with a Mann-Whitney U test on each individual round. If parametric tests are possible, then the Student's t-test will be used.

After this assessment the research question will be examined. When the hypothesis is answered, the question will remain how much effect ambiguity aversion has on the total difference between the treatment group and the control group. There could be more factors that explain this difference. One of the possibilities is that subjects could show a degree of anchoring and adjustment (Tversky and Kahneman, 1974). In the treatment group this could result in participants acting differently based on whether they are above or below the mean value from the 1994 study. In the control group this could be noticeable with participants anchoring to the mean and then following these values. Analyzing the research question will be done by showing significant evidence which factors do affect the differences between the groups and which factors do not these differences.

The analysis of the research question will therefore be in two parts. First, a Mann-Whitney U test will be performed on each individual round. This will be done to compare the absolute differences of the groups to their respective counterpart. This absolute value is the difference between the participants contribution and the mean value from the 1994 study from last round, as this was the information that was shared with the subjects in the following round. Secondly, the treatment group and the control group have to be analysed individually to test whether participants' scores change over the course of the experiment. This will be analysed using the Friedman test.

3.3 Sample

The actual dataset acquired through the online survey consists of 42 completed surveys and 36 partial surveys. These partial surveys will be filtered out of the sample to remove missing data points. Of these 42 completed surveys one participant answered that she was either working or seeking work and thus had to be filtered out aswell. The reasoning behind this decision is that only students were eligible. Another completed survey was preview based, and can therefore not be included in the dataset. The remaining 40 eligible participants concludes the dataset that can be used for statistical analysis. Qualtrics allowed for a randomized and equal distribution over the control group and the treatment group. On top of that, the two subjects that were filtered out were luckily not allocated to the same group and therefore both groups account for 20 subjects.

Table 1

Descriptive statistics of the treatment group and control group

	Treatment group					Control group				
	Median	Mean	Std dev	Min value	Max value	Median	Mean	Std dev	Min Value	Max Value
Gender	0.00	0.40	-	0.00	1.00	0.00	0.45	-	0.00	1.00
Age	22.00	21.35	1.87	18.00	25.00	21.50	21.75	1.12	20.00	24.00
Occupation	2.00	2.00	0.00	2.00	2.00	2.00	2.00	0.00	2.00	2.00
Ethnicity	1.00	1.15	0.67	1.00	4.00	1.00	1.30	1.13	1.00	6.00
Household income	2.00	2.63	1.09	1.00	4.00	2.00	2.18	1.07	1.00	4.00
Political view	4.00	3.15	1.27	1.00	5.00	3.00	2.85	1.27	1.00	5.00

We can see in Table 1 that most statistics are based on the multiple choice answer of the online survey. *Gender* shows the sex of the individual, in which case male and female are numerically expressed by 0 and 1 respectively. The treatment group consisted of 40% male and 60% female, whilst the control group had 45% male and 55% female. The average age of the treatment group was 0.50 years higher than that of the control group. The treatment group also had a higher standard deviation, which can be partly explained by the given information that the minimum value was lower and the maximum value was higher than that of the control group. *Occupation* is a control variable that tests whether all participants are actual student. Median, mean, minimal value and maximum value are all equal as the subjects that did not have the answer ‘Students’ (which was option 2) were filtered out of the dataset. A vast majority of the participants were Caucasian, the treatment group and control group consisted of 95% and 90% Caucasian respectively. *Household income growing up* had the following options: (1 = ‘0-30000’; 2 = ‘30000-60000’; 3 = ‘60000 – 100000’; 4 = ‘More than

100000'; 5 = 'Uncertain / Prefer not to say'). Option 5 was converted to missing data points to prevent it from influencing the descriptive statistics. Average household income growing up was higher in the treatment group. The political views were based on 5 possible answers, which in chronological order were: Left, Middle-Left, Middle, Middle-Right, Right. The answers were quite evenly distributed, with a mean that was around option 3 in both groups.

After these questions the simulated public goods experiment commenced. In Figure 1 we can see that the average contribution in the treatment group was higher than the control group in every round. The initial average contribution is relatively low compared to previous studies. Average mean contributions in standard VCM games started between fourty to sixty percent of the initial wealth and declined as rounds continued (Ledyard & Palfrey, 1995; Merrett, 2012). These were replicable results from many different studies and also many different cultures. Thus, cultural differences should not be a significant factor in these allocation (Gächter, Herrmann and Thöni, 2010). It is therefore interesting to research why the results in this study show a lower initial average contribution and a higher final mean value. This will be discussed further in the conclusion/discussion section.

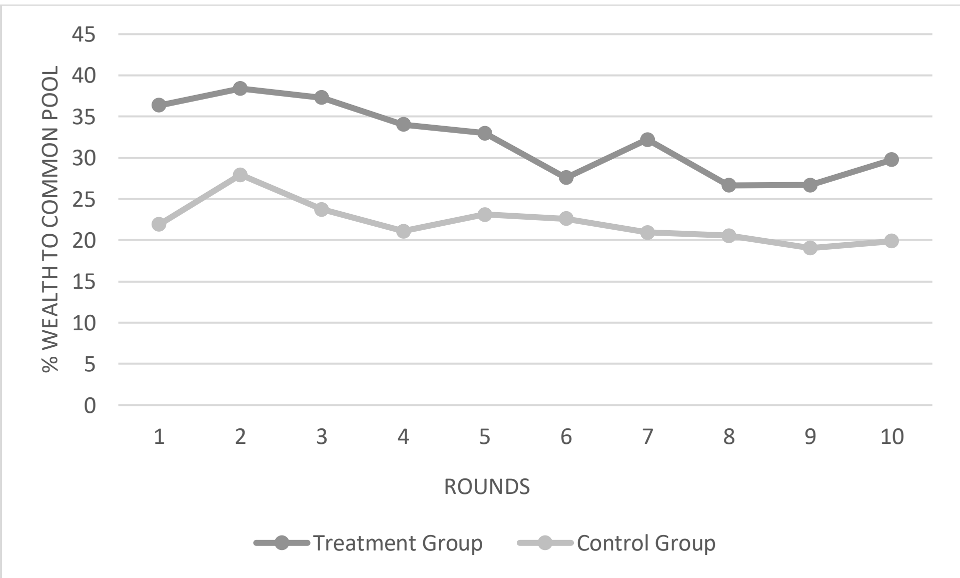

Figure 1. Average contribution of the treatment group and control group individually.

4 Results

4.1 Assumptions of parametric tests

In order to know whether parametric tests or non-parametric tests need to be used, certain assumptions need to be tested. The first assumption is that the means of the populations being compared should follow normal distributions. The second assumption is that the populations being compared should have the same variance. These will be both visually analysed and with a statistical test.

In Appendix A two boxplots can be found of the data, which can be used as a visual representation of the data. From these boxplots it seems fair to assume that the populations follow a normal distribution. The sample is pretty small, and therefore it will remain uncertain whether this assumption does hold. For the second assumption Levene's test will be conducted, both centered at the mean and at the median.

Table 2

Levene's test centered at the mean and median level

Round	Mean of treatment	Mean of control	Levene's test at mean(p-value)	Levene's test at median(p-value)
1	36.35	21.90	1.92 (0.174)	1.29 (0.263)
2	38.40	27.95	0.00 (0.974)	0.00 (0.974)
3	37.30	23.75	0.25 (0.622)	0.23 (0.635)
4	34.05	21.10	0.06 (0.814)	0.05 (0.818)
5	33.00	23.10	0.00 (0.998)	0.00 (0.980)
6	27.60	22.60	0.97 (0.331)	1.06 (0.309)
7	32.20	20.95	0.08 (0.780)	0.09 (0.767)
8	26.65	20.55	0.18 (0.677)	0.18 (0.677)
9	26.70	19.05	0.52 (0.477)	0.48 (0.492)
10	29.75	19.90	0.41 (0.523)	0.31 (0.583)

* $p < 0.05$

** $p < 0.01$

*** $p < 0.001$

In Table 2 we can see the results from Levene's test. The p-values of all rounds show non-significant effects, implying that there is no statistically significant difference in variance between the treatment group and the control group. This would imply that the use of parametric tests can be justified, although the first assumption remains uncertain. Analysis will therefore not be limited to parametric tests, although they are preferred. Parametric tests could be used to seek power in the significance of the results from non-parametric tests.

4.2 Hypothesis

The hypothesis states that the mean contribution will increase when less information is distributed. In order to test this, a Mann-Whitney U test will be performed to compare the results of the treatment group and control group. This non-parametric test allows us to establish whether the mean values of the treatment group are significantly different than those of the control group. This assessment will be done on each round individually on a 95% confidence interval. The nullhypothesis of this analysis is that the means of the groups are equal (H_0: $\mu_1 = \mu_2$).

Table 3

Mann-Whitney U test

Round	**Rank sum Treatment**	**Rank sum Control**	**Adjusted Variance**	**z-value**	**p-value**	**Probability that $\boldsymbol{\mu_1 > \mu_2}$**
1	474.00	346.00	1360.26	-1.735	0.083	0.660
2	459.50	360.50	1362.95	-1.341	0.180	0.624
3	481.00	339.00	1363.46	-1.923	0.055	0.677
4	498.00	322.00	1364.36	-2.382	0.017*	0.720
5	487.00	333.00	1366.67	-2.085	0.037*	0.693
6	458.00	362.00	1363.46	-1.300	0.194	0.620
7	509.00	311.00	1362.95	-2.682	0.007**	0.748
8	457.50	362.50	1362.05	-1.287	0.198	0.619
9	459.50	360.50	1362.44	-1.341	0.180	0.624
10	458.00	362.00	1358.97	-1.302	0.193	0.620

** p < 0.05*

*** p < 0.01*

**** p < 0.001*

In Table 3 the adjusted variance is used as the results have to be adjusted for possible ties. In this table we can see that, on a significance level of *0.05*, the nullhypothesis can be rejected in three rounds. In round seven the nullhypothesis can even be rejected on a 99% confidence interval. This does however imply that in the other seven rounds the nullhypothesis can not be rejected. The one-sided test, where the mean of the treatment group is higher than the mean of the control group, is not significant in any of the ten rounds. After this, a Mann-Whitney U test was run on the mean values of every round. The results showed significant evidence that the average contribution in the treatment group was higher than the average contribution in the control group (*z = 3.553* with *probability = 0.970* on the one-sided test)

Prior to this, the assumptions for parametric tests were tested and do seem to hold. Therefore we can also conduct a Student's t test to research if the treatment group and the control group have significant differences. Rounds will be individually tested to see if there are significant differences in each stage of the experiment. Mean values of the treatment group and the control group will also be analysed to test if there are differences over the entire experiment.

Table 4

Student's t-test

Round	Mean(1) – Mean(2)*	t-value	$\boldsymbol{Pr(diff > 0)}$
1	14.45	1.796	0.040*
2	10.45	1.357	0.091
3	13.55	1.946	0.030*
4	12.95	2.100	0.021*
5	9.90	1.739	0.045*
6	5.00	0.988	0.165
7	11.25	2.142	0.019*
8	6.10	1.126	0.134
9	7.65	1.316	0.098
10	9.85	1.457	0.077

* *p < 0.05*

** *p < 0.01*

*** *p < 0.001*

In Table 4 we can see the results of the Student's t-test. *Mean(1)* represents the mean contribution of the treatment group and *Mean(2)* represents the mean contribution of the control group. There is significant evidence in half of the rounds (5 out of 10) that the mean value of the treatment group is higher than the mean value of the control group (95% confidence level). In order to test if average contribution over the entire experiment is also higher in the treatment group, another Student's t-test has been performed on the mean values of each round. This test showed statistical evidence that the average contribution of the treatment group is significantly higher than the mean contribution of the control group ($t = 6.313$, $p = 0.000$). This indicates that there is some significant evidence to believe that the hypothesis is true.

4.3 Research question

The research question of this paper examines whether ambiguity aversion positively affects the contribution level of participants in a linear public goods game. The comparison between the treatment group and the control group has been analysed, but only on a surface level. It is uncertain to what degree ambiguity aversion influenced the diffences in preferences. Other factors could affect the dataset and thus influence our results. A possible factor that arises in this experimental setup is that subjects could anchor and adjust to the mean value from Isaac et al. (1994) that is shared with them. This would imply that anchoring and adjustment is a partial factor of the gathered results. In order to test this, the absolute differences from the subjects at $round = i + 1$ is valuated against the mean value of $round = i$ from the dataset of Isaac et al. (1994). The treatment group only received knowledge of whether they were above or below this value, while the control group were informed of the actual mean value. In order to test whether anchoring and adjustment might have some effect on the average contribution in each round, the absolute differences of the treatment group will be compared to those of the control group. A Mann-Whitney U test will be performed on the two groups, comparing rounds 2 to 10 individually. An analysis on round 1 can not be conducted as no mean value has been shared with the participants yet.

Table 5

Mann-Whitney U test on absolute differences

Round	Rank sum Treatment	Rank sum Control	Adjusted Variance	z-value	p-value for equal means	Probability that $\mu_1 > \mu_2$
2	375.50	444.50	1362.44	-0.935	0.350	0.414
3	371.00	449.00	1362.82	-1.056	0.291	0.403
4	373.50	446.50	1360.64	-0.990	0.322	0.409
5	374.00	446.00	1362.44	-0.975	0.329	0.410
6	353.50	466.50	1359.36	-1.532	0.125	0.359
7	385.50	434.50	1361.92	-0.664	0.507	0.439
8	418.00	402.00	1353.97	0.217	0.828	0.520
9	416.50	403.50	1357.82	0.176	0.860	0.516
10	398.00	422.00	1355.90	-0.326	0.745	0.470

* $p < 0.05$

** $p < 0.01$

*** $p < 0.001$

We can see in Table 5 that no round has significant values. The nullhypothesis is that the mean absolute differences in the treatment group are equal to that of the treatment group. This nullhypothesis can not be rejected. These findings could imply two things, either anchoring and adjustment have limited effect on the contribution levels of participants or the treatment group and the control group are both affected by an equal level of anchoring and adjustment. It is uncertain which of the two applies here, but in either case this would imply that any significant results found between the groups would not be significantly influenced by the anchoring and adjustment heuristic.

To be even more certain that this is not the case, an unpaired t-test will be conducted on the absolute differences between the treatment group and the control group. If there is not enough significant evidence that these absolute differences are not equal, then this would further imply that the groups were not significantly influenced by the mean values of the dataset from Isaac et al. (1994).

Table 6

Unpaired t-test on absolute differences

Round	Mean(1) – Mean(2)[1]	t-value	$Pr(\|T\| > \|t\|)$
2	-4.65	-0.912	0.368
3	-2.95	-0.660	0.513
4	-1.85	-0.413	0.682
5	-3.30	-0.861	0.395
6	-5.30	-1.601	0.118
7	-1.35	-0.364	0.718
8	0.80	0.209	0.836
9	2.55	0.622	0.538
10	2.85	0.572	0.571

* $p < 0.05$

** $p < 0.01$

*** $p < 0.001$

In Table 6 *Mean(1)* represents the mean of the absolute differences of the treatment group and *Mean(2)* represents the mean of the absolute differences of the control group. We can see in Table 4 that all probabilities are well above $\alpha = 0.05$, which means that the nullhypothesis can not be rejected. There is not enough statistical evidence that the absolute differences of the treatment group and control group compared to the mean value shared with them in the last round differ significantly. We can also see that the mean value of the absolute difference is initially higher in the control group, but after round 8 this dynamic shifts. To test whether there is some significance in the mean absolute difference between the two groups over the entire experiment, these mean values will be compared to each other. An unpaired t-test was conducted, but results remained insignificant ($t = 0.851$ with *probability* $= 0.407$).

A between-subject analysis has now been done on the differences between the groups, but the question remains whether participants show different behavior in different rounds. In order to test if subjects answer differently in each round, a within-subject analysis will be conducted. The Friedman test will be used to analyse this. The nullhypothesis of this test is that average contribution does not differ between the rounds, regardless of what group the individual was assigned to. The results from the treatment group were *Q(9) = 25.46* with *p-value = 0.003*. The results from the control group were *Q(9) = 17.62* with *p-value = 0.040*. Both p-values are less than 0.05 and therefore we can conclude that the results are significant.There is sufficient statistical evidence to reject the nullhypothesis and conclude that contribution significantly differ in different rounds.

5 Discussion

The aim of this paper was to analyse whether ambiguity aversion had a significant effect on the contribution level of participants in a voluntary contribution mechanism. Conducting an online survey made it possible to simulate a VCM public goods game. Every round there was a fixed mean value derived from the dataset of Isaac et al. (1994). The treatment group only received knowledge of whether their contribution was above or below this value. The control group was also shared information on the actual value. The treatment group was thus working with limited information, and was unsure what the mean contribution actually was. The study was based on researching how this uncertainty would be reflected in contribution preferences.

The results found in this study showed that average contribution did increase when less information was shared. These results support the previous findings of Brookshire et al. (1993). They also found that incomplete information has a positive effect on average contribution. Chan et al. (1999) concluded the opposite, as their study showed a decrease in average contribution when less information was shared with the participants. The reasoning behind these contradicting results could be based on the payout structure that was implemented in the experiment. Linear payout structures seem to increase contribution whilst a non-linear payout environment show a decrease in contribution. This has not been tested thoroughly, as the game rules (e.g. the amount of participants per game) in each study were different. In order to be certain, a new study should test whether payout structures show different effects on average contribution while conducted under an incomplete information rule.

In this study we also found that the absolute differences of participants did not significantly differ based on what group they were assigned to. This shows potential future research about the influence of norm compliance. The results from this study imply that this influence may be limited. If norm compliance did have significant effects, then this would be noticeable with significantly lower absolute differences in the control group. They were informed of the actual mean value, so they could show a higher level of norm compliance than the treatment group that only knew the direction of the difference. Future research could continue on these findings to design a field experiment that is purely constructed in finding the degree of norm compliance in a linear public goods game.

Initial average contributions were lower and final average contributions were higher than previous studies (Ledyard & Palfrey, 1995; Zelmer 2003; Cox & Sadiraj, 2007). This shows signs of a weak internal validity of the paper. These results can be based on one of the biggest limitations. No monetary incentives were able to be distributed, as resources for this study were very scarce. Participants might therefore be uninterested in the experiment and not show the same behavior that they would show if it was a true field experiment with actual payout (Kerr, Vardhan & Jindal, 2012). Another conclusion of this paper was that individuals contributed differently in the rounds. These findings were significant for both the treatment group and the control group. It is uncertain if the ambigious setting has different effects in certain phases of the experiment, so this is another possible subject for further research.

Another limitation of the paper is that the external validity seems weak. The dataset only contained students from Rotterdam and therefore results can not be generalized. Most studies in this field of study contain datasets that are obtained in USA (e.g. Isaac et al. (1994) obtained their results from Indiana University and University of Arizona). The geographical and cultural differences can be sufficient enough to not allow results to be compared. Scaling this experiment with monetary incentives would improve the internal and external validity.

Control variables were not included in the statistical analysis, although these variables do contain valuable information. For example, much research has been done on the differences between genders but results remain inconclusive. Other control variables could also be used as explanatory variables for the results, but this has to be further researched.

The decision for an online survey was made to ease participation, resulting in more responses than if the research was conducted using a field experiment. As resources were very scarce, this seemed like the only reliable option to obtain a fairly solid dataset. In order to know whether the results found here are truly based on the factors researched and not based on limitations in the experiment, further research should obtain resources to conduct a real field experiment. For now, results from this paper can be used as a stepping stone for further research and guide studies in the right direction, as even with all limitations there does seem to be some significance in the findings.

6 Conclusion

The hypothesis that was researched in this paper stated that average contribution of participants in a linear public goods game would increase when they were presented with uncertainty through incomplete information. The results of the online survey showed statistical evidence in favor of this hypothesis, as average contribution was significantly higher in the treatment group than the control group. Significant differences were also tested on each round individually, where half of the rounds (5 out of 10) were significantly higher in the treatment group. Round three, four and five were part of this group, which could imply that the effects of ambiguity are mostly noticeable in the early to middle phases of the experiment. There were quite some inconclusive results though, as the study was fairly small scale and did not contain any monetary incentive.

Other findings were obtained by analysing if other factors influenced the results. Not enough significant results were found on the absolute differences of both groups when compared with the mean value from the dataset of Isaac et al. (1994). Therefore we can conclude with some certainty that anchoring and adjustment did not significantly affect the contribution level of participants. We found that results varied throughout the rounds, which could imply that the effect of the ambigious settings are different throughout the experiment. Further research is necessary to establish this and to examine everything surrounding these results.

When one combines all the statistical analysis from this paper we can conclude that there is significant evidence, showing that incomplete information has a positive effect on average contribution in a linear public goods game. Although it remains uncertain whether this is truly caused purely by ambiguity aversion, progress has been made in this specific field as previous studies remain insufficient. This study shows initial results, but further studies are necessary to support these findings and to build upon them. Some of the practical implications of this paper is that VCM-based charities can implement some form of incomplete information when sharing information surrounding other donors' contribution. These findings are supported by the conclusion from Chen, Chen and Wang (2019). These implications do not hold in every charitable organization. There are plenty of VCM structures that benefit from complete information, such as the categorical structure where every donation is publicized (Harbaugh, 1997). The implications of this paper are mostly meant for VCM structures that are based around donors’ own approval of donating than structures that are based around donating for the societal approval of the donation.

7 Reference list

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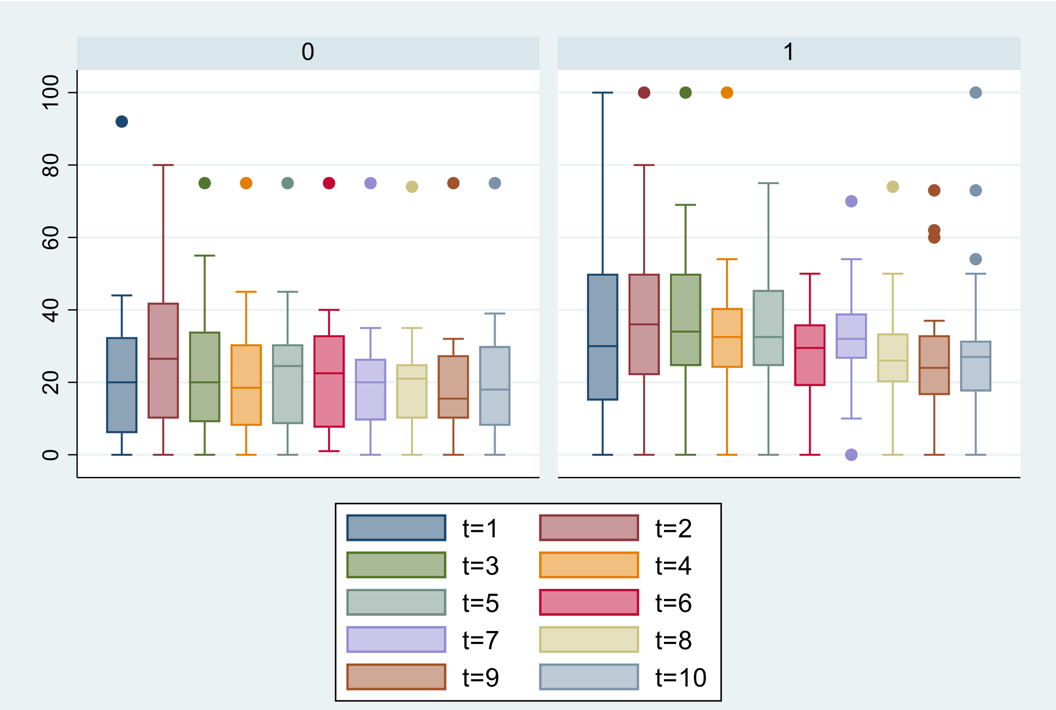
8 Appendix

Appendix A:



Boxplots of the experiment with average contribution level on the y-axis and rounds on the x-axis. Graph 0 represents the control group and Graph 1 represents the treatment group.