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# Individual Decision Making in Exogenous Targeting Instrument Experiments

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**Abstract.**
The experimental treatments analysed in this paper are simple in that there is a unique Nash equilibrium resulting in each player having a dominant strategy. However, the data show quite clearly that subjects do not always choose this strategy. In fact, when this dominant strategy is not a "focal" outcome it does not even describe the average decision adequately. It is shown that average individual decisions are best described by a decision error model based on a censored distribution as opposed to the truncate regression model which is typically used in similar studies. Moreover it is shown that in the treatments where the dominant strategy is not "focal" dynamics are important with average subject decisions initially corresponding to the "focal" outcome and then adjusting towards the Nash prediction. Overall, 66.7% of subjects are consistent with Payoff Maximization, 27.8% are consistent with an alternate preference maximization and 5.6% are random. (JEL C72, C92, D70)

**Keywords:** Quantal Response, Moral Hazard In Groups, Exogenous Targeting Instruments, Experiments

## 1. Introduction

In the public good environment, with linear payoff functions, the payoff maximizing dominant strategy typically is to contribute nothing, but partial contributions are consistently observed. A similar phenomenon is observed in the negative externality experiment investigated by Spraggon (2002a; 2002b). Subjects are assigned randomly to a payoff function which results in the dominant strategy Nash prediction either on the lower bound of the decision space (as in the standard linear public goods experiment) or in the interior of the decision space. As in the linear public good experiment, those whose Nash decision is to choose zero choose significantly higher numbers on average. However, those whose Nash decision is in the interior

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of the decision space choose significantly lower numbers on average. Typically over contribution in the public good environment is attributed to altruism (e.g. Willinger and Ziegelmeyer 2001; and Anderson et al. 1998) as choosing larger numbers makes others better off. Saijo and Nakamura (1995) reversed the standard public good experiment so that full contribution is the Nash equilibria. They found that in this case subjects contributed less than the Nash prediction and attributed this behavior to spite.[1] In the negative externality environment choosing larger numbers makes others worse off while choosing lower numbers makes others better off. As a result we observe some subjects who behave altruistically and some who behave spitefully, but this behavior depends on their payoff function which was assigned randomly.

Ledyard (1995) suggests that subjects can be classified into those whose decisions can be explained by either payoff or alternate preference maximization and decision error and those whose decisions seem random. This paradigm is applied to the negative externality experiment discussed in Spraggon (2002a; 2002b). This experiment provides a unique opportunity to test whether the various theories suggested in the literature to explain non-Nash decisions for two reasons. The first is that the different frame allows us to test models which have been shown to explain individual decision making in a slightly different environment. The second is that a quadratic payoff function has been used in this experiment, and the Nash decision has been varied throughout the decision space.

In the standard public good environment it is difficult to identify whether the partial contributions are due to incompletely controlled preferences or decision error. When the dominant strategy Nash equilibrium is on a boundary –as it is in the standard linear public good environment– both preference and decision error hypotheses predict the same behaviour. To discriminate between these two explanations, the parameters of the experiment must be varied (Palfrey and Prisbrey, 1997). Palfrey and Prisbrey use the simple linear public good environment and vary the parameters faced by each subject in each period. Anderson et al. (1998) use the variation of parameters across different experiments to identify the effects of the different hypotheses. Both papers find that both preference explanations and decision error are important in how subjects make their decisions. Other authors have complicated the simple public good environment by introducing payoff functions that are nonlinear, making partial contribution the payoff maximizing dominant strategy (Willinger and Ziegelmeyer, 2001; Laury and Holt, forthcoming; Keser, 1996; Sefton and

[1] Brunton et al. (2001) replicate the Saijo and Nakamura (1995) experiment and call into question the spite explanation by also testing for the subjects value orientations.

Steinberg, 1996; Chan et al., 1996). This allows different effects of errors and preferences to be identified. Errors should result in a distribution of decisions that is symmetric about the payoff maximizing dominant strategy Nash equilibrium (barring any boundary effects) while preferences should result in the peak of the distribution of subjects' contributions being different from the payoff maximizing decision (Anderson et al. 1998). These studies suggest that both preferences and decision error are important in how subjects make their decisions.

This paper differs from the previous literature in that it is framed as a public bad rather than a public good. Authors such as Park (2001), Willinger and Ziegelmeyer (1999), Sonnemans et al. (1998) and Andreoni (1995) show that decisions are closer to the dominant strategy Nash equilibrium in public bad than they are in public good experiments. Second, where previous studies use a truncated version of the quantal response equilibrium model introduced in McKelvey and Palfrey (1995) and used by authors such as Offerman, Schram and Sonnemans (1998), Anderson, Goeree, and Holt (1998) and Willinger and Ziegelmeyer (2001). We introduce a censored version of the quantal response equilibrium model.

In this environment, we find that decision making is best described by a simple heuristic in early periods followed by adjustment towards the dominant strategy Nash equilibrium. Moreover, it is argued that the censored form of the quantal response equilibrium model is more consistent with the data both theoretically and empirically. However, at the individual level, decision making is consistent with the proportions of Nash decision making, alternate preferences and randomness suggested by Ledyard (1995).

Section two of this paper presents the model underlying the experiment and the predictions if subjects are payoff maximizers. Also, in section two the logit quantal response and Tobit models are presented. Section three summarizes the predictions of these models of preferences and decision error. Section four discusses the consistency of the individual level data from the experiments with the predictions of the preference models and the preference models augmented by the decision error models. Finally, section five summarizes and concludes the paper.

## 2. The Moral Hazard in Groups Experiment

The experiment is based on a standard moral hazard in groups problem. Subjects choose a decision number, the larger the number the higher the subject's private payoff. A principal, who would like to induce the agents to reduce their decision number, uses a contract so that the higher the sum of the decisions of everyone in the group the lower the group payoff. This is analogous to Segerson's (1988) solution to the non-point source pollution problem as well as the common pool resource problem; the more of the resource the subject appropriates for herself the higher her profits but the lower the payoff to society. An individual's total payoff function is given by the sum of the private payoff function (terms one and two) and the group payoff function (term three):

$$\pi_n = 25 - 0.002(x_n^U - x_n)^2 + 0.3(150 - \sum_{n=1}^{6} x_n) \tag{1}$$

where $x_n$ is individual $n$'s decision number, and $x_n^U$ is the upper limit on individual $n$'s decision number. There are two treatments. In the first, all of the subjects are "medium capacity" in that they choose their decision numbers between 0 and 100 ($x_n^U = 100$). These sessions are referred to as homogeneous. In the second, half of the subjects are large capacity who choose their decision numbers between 0 and 125 ($x_n^U = 125$) and half are small capacity who choose their decision number between 0 and 75 ($x_n^U = 75$).[2] In the homogeneous treatments subjects were informed that they were all choosing between 0 and 100, while in the heterogeneous treatments subjects were told that three of the people in their group choose decision numbers between 0 and 75 and three choose decision numbers between 0 and 125. Moreover, subjects were given tables representing their own payoff function and in the heterogeneous sessions the payoff function of someone of the other type.

Each experimental session involved one group of six subjects indexed $n = 1 \ldots 6$. Each subject made twenty-five decisions for each of two treatments in each session. Subjects had full information as to the number of people in the group, the payoff functions of the others and the number of periods. The subjects

[2] The homogeneous treatments are described in more detail in Spraggon 2002a, and the heterogeneous treatments are discussed in Spraggon 2002b.

were also informed that the maximum possible group total was six-hundred.[3] This treatment is referred to as the Tax-Subsidy instrument in Spraggon (2002a; 2002b). This paper uses data from the periods which were presented to subjects with no previous experience in this environment. Subjects were randomly assigned a capacity which determined their private payoff for each possible decision number.[4]

The Nash equilibrium for the stage game is trivial to calculate. A subject's best response is to choose a decision number which maximizes the payoff function (1). Notice that this function is separable in the individual's decision ($x_n$) and the decisions of the other subjects. The first order condition for this maximization is

$$\frac{d\pi_n}{dx_n} = 0.004(x_n^U - x_n^*) - 0.3 = 0 \tag{2}$$

which results in a dominant strategy for each subject given by $x_n^* = x_n^U - 75$. Thus, the Nash equilibrium decision numbers are 0, 25 and 50 for small, medium and large capacity subjects, respectively. For both the homogeneous and heterogeneous treatments, if all subjects choose the Nash equilibrium decision number, the group total will be equal to the target level of 150. Since this is the unique Nash equilibrium in the stage game it is also the unique subgame perfect equilibrium in the finitely repeated game (Osborne and Rubinstein 1994, pp. 157-158).

### 2.1. Alternate Preferences

There are many different preference explanations for why people deviate from the Nash equilibrium strategy. Most of these explanations are focused on non-Nash contributions in public good experiments. People could contribute to a public good (when it is not in their financial interest) because they receive a non-monetary reward simply from contributing or from making others better off. The former is referred to as "warm-glow", the latter is referred to as altruism (Palfrey and Prisbrey, 1997). Other authors such as Fehr and Schmidt (1999) and Bolton and Ockenfels (2000) have suggested that a subjects relative payoff either to the maximum or minimum payoff in the Fehr and Schmidt paper or to the average payoff in the Bolton

[3] The maximum possible decision number is the sum of the maximum possible decision numbers for everyone in the group (600, $6 \times 100$ in the homogeneous treatments and $3 \times 75 + 3 \times 125$ in the heterogeneous treatments)

[4] When subjects arrived for the experiment they randomly chose a numbered card from a pile. The number determined their capacity.

Table I. Predictions of Payoff Maximization and Alternate Preference Explanations

| Treatment | Payoff Maximization | Altruism | Equity in decision | Fehr & Schmidt | Bolton et al. | Value Orientations | | |
|---|---|---|---|---|---|---|---|---|
| | | | | | | Cooperators | Individualists | Competitors |
| Large Capacity | 50 | <50 | <50 | $\lesseqgtr$ 50 | 50 | <50 | 50 | >50 |
| Medium Capacity | 25 | <25 | 25 | $\lesseqgtr$ 25 | 25 | <25 | 25 | >25 |
| Small Capacity | 0 | 0 | >0 | >0 | 0 | 0 | 0 | >0 |

Columns 2 through 9 refer to the different preference explanations discussed in the text.

and Ockenfels paper may effect decision making. Moreover, authors such as Hackett, Schlager and Walker (1994) Chan et al. (1997) and Rapoport and Suleiman (1993) suggest that an individual's decision may depend on the decisions made by other subjects. Another attempt to explain how people make decisions in these types of experiments is the value orientation method investigated by authors such as Offerman et al. (1996), Park (2001) and Buckley et al. (2002). Each of these models make different predictions which are summarized in Table 1 and discussed below.

If altruism or warm-glow is important, subjects will choose decision numbers which are less than the payoff maximizing prediction since choosing lower decision numbers increases the group component of the payoff function $(0.3(150 - \sum_{n=1}^{6} x_n))$. If warm-glow is important then the choice of decision number should be independent of the number of people it will benefit while if altruism is important then increasing the number of people who enjoy the public good should lead to higher contributions. Since I do not vary the number of subjects I cannot identify separate effects of altruism and warm glow. Moreover, Goeree et al. (2002) suggest that contributions rise with group size which is consistent with altruism rather than warm-glow. As a result, I ignore warm-glow and concentrate on altruism. In the present environment reducing one's decision number from the maximum makes the other people in the group better off in the same way as contributing to a public good.

The Fehr and Schmidt (1999), Bolton and Ockenfels (2000), Rapoport and Suleiman (1993), Hackett, Schlager and Walker (1994), and Chan et al. (1997) papers are all concerned with different types of equity. The first two papers use models based on equity in terms of utility while the final three papers advocate

models based on equity in terms of the decision numbers chosen (which corresponds to appropriation or contribution in these environments). We will refer to the former as equity in payoff and the latter as equity in decision. The Hackett, Schlager and Walker (1994) paper points out that there are many different ideas of equity which subjects might use to choose their decision numbers in the common pool resource environment. They might feel that they should all choose the same decision number, or the same proportion of their maximum decision number, or reduce their decision number from the maximum by the same amount, or reduce from their maximum decision number by the same proportion. The Rapoport and Suleiman (1993) and Chan et al. (1997) papers focus on the relationship between the individuals decision and the average decision of the rest of the subjects in the group. For the homogeneous treatments, all of these equitable solutions result in the subjects choosing the Nash equilibrium prediction. For the heterogeneous treatments, the Nash equilibrium prediction of the payoff maximization model is an equal reduction from the maximum decision number. If subjects choose the same decision number, they would all choose 25. If they reduce their decision number by the same proportion or choose the same proportion of their decision number, the small capacity subjects would choose 19 and the large capacity subjects would choose 31. We refer to all subjects choosing 25 as the 'focal' or simple heuristic solution as it can be arrived at by dividing the target (150) by the number of people in the group. The Fehr and Schmidt and Bolton and Ockenfels papers are concerned with relative payoffs. In both the homogeneous and heterogeneous treatments the Nash equilibrium results in equal payoffs for all subjects. If subjects prefer to have either the highest or lowest relative payoffs they should choose decision numbers which are higher or lower than the Nash prediction. Thus the Bolton and Ockenfels model predicts that subjects should choose the Nash equilibria while the Fehr and Schmidt model provides an explanation for why subjects may choose decision numbers which are higher or lower than the payoff maximizing Nash equilibria.

The value orientation hypothesis used by authors such as Offerman et al. (1996), Park (2001) and Buckley et al. (2001) show that subjects can be classified into cooperators, individualists and competitors. In this experiment cooperators are likely to reduce their decisions below the Nash prediction which makes everyone in the group better off, individualists should choose the Nash prediction and competitors should choose decision numbers in excess of the Nash prediction which makes everyone worse off.

### 2.2. Logit Quantal Response Equilibrium

Authors such as Offerman et al. (1998), Anderson, Goeree, and Holt (1998) and Willinger and Ziegelmeyer (2001) apply the McKelvey and Palfrey (1995) quantal response equilibrium to public good games. This theory is based on the assumption that subjects make mistakes or are uncertain with respect to their utility. Further, subjects are assumed to make their decisions under the belief that others also make mistakes or are uncertain about their utility from a given strategy. The probability of a strategy being chosen is modeled as depending on the expected payoff of the strategy. Strategies with higher expected payoffs are played with higher frequencies than strategies with lower expected payoffs. The distribution of individual decisions is modelled as the truncated logistic distribution

$$f_n(x_n) = Kexp(\pi_n^e(x_n)/\mu) \tag{3}$$

where $K$ is a constant chosen such that the density integrates to one and $\mu$ parameterizes the importance of individual errors. As the decision error parameter ($\mu$) approaches zero, the quantal response equilibrium approaches the Nash equilibrium prediction of the payoff maximizing model and as $\mu$ approaches infinity, the quantal response model predicts random play.

For the quadratic payoff function discussed in this paper the quantal response model can be written as:

$$f_n(x_n) = K'exp(-0.002(x_n - x^*)^2/\mu) \tag{4}$$

where $x^*$, the utility maximizing decision, is the peak of the distribution and $K'$ is a constant which depends on the decisions of other subjects. Appendix A.1 provides a detailed derivation of this function. Anderson et al. (1998) show that for expected payoff functions of this form, there is a unique quantal response equilibrium and that the expected contribution under this equilibrium is "sandwiched" between the equilibrium outcome without decision error and half of the endowment. This is a direct result of the assumption that more costly errors are less likely to be observed. As shown in Figure 1, the peak of the distribution is at the preference maximizing decision for medium capacity subjects. Figure 1 also shows the importance of the decision error parameter ($\mu$). Notice that when $\mu = 1$ there is a very definite peak and as $\mu$ approaches infinity the distribution approaches a uniform distribution. As a result, this model's

prediction depends on the decision error parameter as well as the subject's capacity, and the subject's preferences for altruism and equity (which effect $x^*$, the peak of the distribution).

The assumption that the distribution of individual decisions is truncated is not innocuous. Greene (2000) describes truncated data as data which is "drawn from a subset of a larger population of interest" (p. 896) as opposed to censored data where the actual observation may differ from the true observation. In terms of the experimental data presented here, truncation would best describe the data if the subjects were selected from a group of people who would never want to choose below zero or above their maximum decision ($x_n^U$). Alternatively, the data is best described by censoring if subjects who might like to choose numbers below zero or above their maximum ($x_n^U$) choose zero or their maximum ($x_n^U$) instead.[5] Whether subjects behave as if the only reasonable decisions are between zero and their upper bound ($x_n^U$) or as if they would rather choose decisions outside of the range is at least partially an empirical question. As a result, both a truncated and a censored distribution are fit to the data and the results are presented in the next section.

The censored distribution differs from the truncated distribution in that instead of normalizing all of the frequencies in the decision space, the density is estimated separately for observations at the lower bound, observations in the middle of the density, and observations at the upper bound. The distribution of decisions in this case is given by

$$g_n(x_n) = \begin{cases} \Phi(-x^*/\sqrt{\mu/2k}) & if\ x_n = 0 \\ (exp[-k(x_n - x^*)^2/\mu])/(\sqrt{2\pi}\sqrt{\mu/2k}) & if\ 0 < x_n < x_n^U \\ 1 - \Phi((x^{max} - x^*)/\sqrt{\mu/2k}) & if\ x_n = x_n^U \end{cases} \tag{5}$$

where $\Phi$ is the cumulative standard normal distribution. More information on the censored distribution is provided in Appendix A.2.

As suggested in the previous section if subjects have preferences differing from simple payoff maximization then $x_n^*$ will differ from the prediction of payoff maximization. Indeed the peak of the distribution

[5] Choosing above or below the boundary is not necessarily irrational. Consider a subject with either extreme altruism or a strong preference for the group total to equal the target (150). They may receive utility from choosing decision numbers below zero, even though this may result in negative payoffs. A similar argument can be made for those who might like to choose numbers greater than the boundary.

of individual decisions should be the utility maximizing decision number. Since subjects were randomly assigned to a role there is no reason to believe that preferences should not be consistent across the treatments. As a result, the estimation of the peaks of the quantal response model will suggest which types of preferences are most consistent with the data.

## 3. Results

### 3.1. Average decisions are best described by the censored form of the Quantal Response Model and equity in decision.

The parameters of the decision error model (the preference maximizing decision ($x^*$) and error parameter ($\mu$)) can be estimated by maximum likelihood for both the truncated and censored distributions. Table II shows the estimated parameters, mean of the estimated distribution, and the mean log-likelihood for each subject type and for the truncated and censored models.

For the large capacity subjects, the truncated model has a large error parameter ($\mu = 4.3$) and the estimated peak ($x^* = 20.95$) is low. The censored distribution has a much lower error parameter ($\mu = 2.35$) and the estimated peak ($x^* = 35.18$) is closer to the mean decision number (35.29). The means of both of these estimated distributions are not significantly different from the observed mean. Figure 2 shows the distributions for large capacity subjects. Notice that the peak of the censored distribution is more consistent with the data as the peak of the truncated distribution is low so as to fit the observations around zero.

For the small capacity subjects, the truncated model is only able to converge if the estimated peak is constrained at zero, however both parameters are able to be estimated from the censored distribution. Figure 3 shows that the censored distribution is able to account for both of the spikes at the end points as well as the peak in the middle of the decision space. This again suggests that the data are more consistent with the censoring hypothesis and that the truncated distribution is biased.

Finally, notice that for the medium capacity subjects both the truncated and the censored distributions have similar estimations for the error parameter ($\mu$) and the peak of the distribution ($x^*$). The error parameter is slightly smaller for the censored distribution and the estimated peak is closer to the observed

Table II. Predictions from Estimations with Decision Error Model

| Treatment | Estimated $\mu$ | Estimated $x^*$ | Mean Fitted Distribution | Mean Log-likelihood |
|---|---|---|---|---|
| Large Capacity, Observed Mean: 35.293 | | | | |
| Truncated | 4.3010 | 20.9528 | 35.3 | -3.53967 |
| | (0.8884) | (5.5683) | | (225 obs) |
| Censored | 2.3468 | 35.1784 | 35.97 | -4.50947 |
| | (0.1795) | (1.4508) | | (225 obs) |
| Medium Capacity, Observed Mean: 26.407 | | | | |
| Truncated | 1.0688 | 24.0232 | 26.41 | -4.03231 |
| | (0.1029) | (1.0167) | | (450 obs) |
| Censored | 0.8679 | 26.2678 | 26.49 | -4.02168 |
| | (0.0547) | (0.6990) | | (450 obs) |
| Small Capacity, Observed Mean: 21.529 | | | | |
| Truncated | 4.1492 | 0 | 24.54 | -4.11492 |
| | (0.5104) | (0) | | (225 obs) |
| Censored | 2.4907 | 18.9855 | 22.04 | -3.94358 |
| | (0.2725) | (1.7105) | | (225 obs) |

* the numbers in parenthesis are standard errors.

mean. Notice in Figure 4 that as was the case for the large and small capacity the truncated distribution is higher than the censored for low decision numbers, an effect which is picked up only at the end point for the censored model. This also suggests that the censored model better describes the data.

The estimation of the censored quantal response model suggests that the preference maximizing decision number for small capacity subjects is statistically significantly greater than the payoff maximizing Nash prediction, equal to the payoff maximizing Nash prediction for the medium capacity subjects and statistically significantly less than the payoff maximizing Nash prediction for the large capacity subjects. Table I shows that these results are only consistent with equity in decision. The results do not seem consistent with

the other models in that these models predictions are not consistent across the different treatment groups (see Table 1). Since subjects are assigned to the treatment group randomly there is no reason to believe that more altruistic individuals were assigned to the role of large capacity subjects than were assigned to the role of small capacity subjects. Moreover, we would need an almost perfect mix of altruistic/negative altruistic subjects to obtain the results we see for the medium capacity subjects. This same argument can be made for the Fehr and Schmidt (1999) and Value Orientations hypotheses. Equity in decision is the only model which predicts that some groups will choose numbers greater, some will choose less and some will choose numbers that are equal to the Nash prediction.

### 3.2. Dynamics are important: subject's initial decisions correspond to a simple heuristic and adjust toward the Nash prediction over time

The basic result is shown in Table III and Figures 5 through 7. For large and small capacity subjects their decision numbers are initially very close to 25 and then adjust towards the Nash prediction (50 and 0) over time. The mean decision number for medium capacity subjects is consistently close to 25 across all periods. This suggests that on average subjects make their initial decision using the simple heuristic (the target divided by the number of people in the group), and then the incentives induce the large capacity subjects to increase their decision numbers and the small capacity subjects to reduce their decision numbers. Notice that the large capacity subjects converge more closely to the Nash prediction than do the small capacity subjects.

Table IV presents the results of the convergence regression suggested by Noussair et al. (1995). Notice that individual decisions are not significantly different from 25 for any of the subject types in the early periods and that only the time trend for the large capacity subjects is statistically significant.[6] The regression analysis was conducted using both White's (1980) correction method and a random effects model (Green 2000) to account for the interdependence of the observations. Recall that for both subject types increasing your decision numbers increases your private payoff and decreases your group payoff while decreasing your decision numbers decreases private payoff and increases your group payoff. Thus, the small capacity subjects reducing their decision numbers by less than the large capacity increase their decision

[6] A simple Tobit regression with dummy variables for the three different subject capacities and this dummy crossed with period also provides the same results.

Table III. Mean and Median Decision Numbers by Capacity

| Treatment | Mean Period 1 | Mean All Periods | Mean Period 25 | Median Period 1 | Median All Periods | Median Period 25 |
|---|---|---|---|---|---|---|
| Large Type | 20.44 | 35.29 | 51.89 | 25 | 30 | 50 |
| | (3.99) | (1.57) | (10.22) | (3.99) | (1.57) | (10.22) |
| | [9] | [225] | [9] | [9] | [225] | [9] |
| Medium Type | 26.72 | 26.41 | 32.89 | 25 | 25 | 25.5 |
| | (4.88) | (0.674) | (4.82) | (4.88) | (0.674) | (4.82) |
| | [18] | [450] | [18] | [18] | [450] | [18] |
| Small Type | 24.89 | 21.53 | 19.56 | 15 | 20 | 5 |
| | (8.69) | (1.41) | (9.06) | (8.69) | (1.41) | (9.06) |
| | [9] | [225] | [9] | [9] | [225] | [9] |

* the numbers in parenthesis are standard errors and the number in square brackets is the number of observations.

Table IV. Random Effects Tobit Regression of Convergence Model for Individual Decisions

| Number of Observations = 900 | | | Log Likelihood = -3755.43 | | |
|---|---|---|---|---|---|
| | | Coefficient | Std. Error | z | $P > \|z\|$ |
| Large/t | $\beta_{11}$ | 15.22 | 5.70 | 2.67 | 0.008 |
| Small/t | $\beta_{12}$ | 27.24 | 5.774 | 4.72 | 0.000 |
| Medium/t | $\beta_{13}$ | 26.96 | 4.06 | 6.64 | 0.000 |
| Large(t-1)/t | $\beta_{21}$ | 38.81 | 1.73 | 22.47 | 0.000 |
| Small(t-1)/t | $\beta_{22}$ | 18.31 | 1.759 | 10.40 | 0.000 |
| Medium(t-1)/t | $\beta_{23}$ | 26.05 | 1.273 | 20.47 | 0.000 |

$x_n = \beta_{11}L/t + \beta_{12}S/t + \beta_{13}M/t + \beta_{21}L(t-1)/t + \beta_{22}S(t-1)/t + \beta_{23}M(t-1)/t + \epsilon$, standard errors adjusted for clustering on session. Where L represents large capacity subjects, S represents small capacity subjects,M represents medium capacity subjects, and t represents period.

number is consistent with the hypothesis that subjects receive more dis-utility from having a payoff below the average than they do from having a payoff which is above average (Fehr and Schmidt (1999); Kahneman and Tversky (1979)).

### 3.3. There is considerable Heterogeneity in Individual Decisions

The preceding analysis is concerned primarily with individual decision making on average. As Ledyard (1995) suggests, decisions differ by individual. Figures 8 through 10 describe the individual decisions for each subject by capacity.[7] These figures show a great deal of heterogeneity between individuals.

Figure 8 describes the individual decisions of the large capacity subjects. Notice that only one of the subjects' (52) choices are close to the Nash prediction for a significant number of periods. Subjects 42, 53, 63 and possibly 61 seem to adjust to the Nash prediction by the final period. Subjects 51 and 62 consistently chose 25 or close, while subject 41 chose close to zero and eventually increased their decision to just under 20. Subject 43's average decision is 41.68 and the decisions ranged from zero to 50 in a pattern that seems random. Hence Nash or convergence to Nash is a good predictor for 5 of the 9 subjects while equity in decision or extreme altruism seems to explain the decisions of 3 of the 9 and the final subject appears to have been choosing randomly. Moreover, the decisions of subjects 42, 52, 53, 61, and 63 (5 of 9) start close to the simple heuristic (25) and converge toward Nash.

For the small capacity subjects (Figure 9) one chose the Nash decision every time (46), one is very close in all periods (64), one chose Nash in most periods (54) and one converges towards it (65). One subject initially chose the Nash prediction and then converges above 25 (44); Subjects 55, 56 and 66 choices are close to 25 in most periods while subject 45 chose close to her maximum and then falls but not quite to the Nash level over time. Thus we have four subjects whose decisions are best described by the Nash prediction and five whose decisions are consistent with some other preference explanation. Four of the nine start at 25 and then converge to the Nash prediction.

For the medium capacity subjects 15 of 18 (subjects 11, 12, 13, 16, 21, 22, 23, 24, 25, 26, 31, 32, 33, 34 and 36) chose decisions that are quite close to the Nash prediction. Subjects 14 and 35 converged away

[7] Fischbacher et al. (2001) use similar figures, except they solicit reaction curves as opposed to the figures here which are actual decisions.

from the Nash prediction and subject 15's decisions were quite random. Thus fifteen of eighteen conformed to the Nash prediction, two chose according to some other preference and one was random.

Thus, overall we have twenty-four of thirty-six (66.7 percent) subjects whose decisions are best described by the Nash prediction, ten of thirty-six (27.8 percent) who are consistent with some other preference explanation and two of the thirty-six (5.6 percent) whose decisions seem random. This is consistent with Ledyard's (1995) 50 percent, 40 percent, 10 percent observation across "many subject pools" (p. 173) and the comparisons between public good and public bad (Andreoni, 1995; Sonnemans et al., 1998; Park, 2001; Willinger and Ziegelmeyer, 1999) which suggest that dominant strategy play is more frequently observed in public bad environments. Moreover, 9 of 18 (50 percent) of the subjects whose Nash decision was not the simple heuristic (25) (large and small capacity subjects) start with this rule and then adjust towards Nash over time. This suggests that payoff-maximizing Nash behavior is a far better predictor of individual decision making than the earlier analysis indicates.

## 4. Conclusions

This paper has attempted to provide some explanation for the anomalous decision making observed in the negative externality experiments presented in Spraggon (2002a and 2002b). This behavior differs from that observed in the standard public good framework in that subjects with one payoff function choose decision numbers that are less than the Nash prediction while subjects with another payoff function choose decision numbers that are greater than the Nash prediction. Despite the differences in the two environments individuals behavior is remarkably consistent with the proportions of payoff maximizers, other preference maximizers and those whose decisions are random suggested by Ledyard (1995). However the deviations are more consistent with equity in decision than altruism which is the predominant explanation for anomalous behavior in public good games. Moreover, it is shown that the data is more consistent with a censored form of the quantal response equilibrium model than the truncated version which is becoming standard in the literature.

Clearly, this paper suggests that the censored form of the quantal response equilibrium model should be applied to the data analysis of other experiments. Indeed, in the distributions of individual decision making

presented by Willinger and Ziegelmeyer (2001) for their public good experiment (Figure 1, p. 137) there are obvious peaks at the upper bound of the decision space for all of their treatments. That the data presented here is consistent with equity in decision does not seem as transferable to the public good case. In this experiment the subjects are told that there is a target and so taking that target and dividing by the number of people in the group is an obvious and simple way to choose a decision number. This is not the case in the standard linear public good. Although, in games where there is an obvious and simple way to choose a decision number, we should expect subjects to make this decision initially and then adjust towards the Nash equilibrium subject to the Fehr and Schmidt (1999) model which suggests that subjects prefer their payoff to exceed the average payoff of their reference group. Finally, it may be interesting to investigate how consistent Ledyard's ballpark classification of subjects as Nash payoff maximizers, alternative payoff maximizers, and those who play randomly is across different subject pools and experiments.

# Appendix

## A. Mathematical Appendix - The Decision Error Model

### A.1. The Truncated Model

The quantal response decision error model assumes that decisions are distributed logistically. This results in the following density function for individual decisions:

$$f_n(x_n) = \frac{exp(\pi_n^e(x_n)/\mu)}{\int_0^{z_n} exp(\pi_n^e(x_n)/\mu)\partial x_n} \tag{6}$$

(Anderson, Goeree, and Holt, 1998). This is a truncated logistic distribution. For the Tax-Subsidy contract $\pi_n^e$ is given by equation (1) and as a result the quantal response equilibrium distribution is given by

$$f_n(x_n) = \frac{exp[25 - 0.002(x_n^U - x_n)^2 + 0.3(150 - X)]/\mu}{\int_0^{z_n} exp[(25 - 0.002(x_n^U - x_n)^2 + 0.3(150 - X))/\mu]\partial x_n}. \tag{7}$$

Since $e^{a+b} = e^a e^b$ terms that do not depend on $x_n$ can be eliminated from $f(x_n)$. Completing the square of $\pi_n^e$ simplifies $f_n(x_n)$

$$(25 - 0.002(x_n^U - x_n)^2 + 0.3(150 - X))$$

$$= 25 - 0.002((x_n^U)^2 - 2x_n x_n^U + x_n^2) - 0.3x_n - 0.3\sum_{j \neq n} x_j + 0.3(150)$$

$$= (0.004x_n^U - 0.3)x_n - 0.002x_n^2 + C$$

(the constant will be eliminated)

$$= 0.002[2(x_n^U - 0.3/0.004)x_n - x_n^2 + C']$$

(completing the square)

$$= -0.002[(x_n - (x_n^U - 0.3/0.004))^2 - (x_n^U - 0.3/0.004)^2 + C']$$

$$= -0.002(x_n - (x_n^U - 0.3/0.004))^2 + C''. \tag{8}$$

Notice from the first order condition of the individuals payoff function (2) $x_n^U - 0.3/0.004 = x_n^*$. Therefore

$$f_n(x_n) = \frac{exp(-0.002(x_n - x_n^*)^2)/\mu)}{\int_0^{z_n} exp(-0.002(x_n - x_n^*)^2)/\mu)\partial x_n}. \tag{9}$$

Also notice that the denominator has a similar functional from to the normal probability density function

$$\int_{-\infty}^{\infty} \frac{1}{\sqrt{2\pi}} \frac{1}{\sigma} exp(-1/2(x - \bar{x})/\sigma^2)\partial x = \Phi(\frac{A - \bar{x}}{\sigma}). \tag{10}$$

In fact if $\bar{x} = x^*$ and $2\sigma^2 = \mu/0.002$

$$\sqrt{2\pi}\sqrt{(\mu/2(0.002))} \int_0^{x_n^U} \frac{1}{\sqrt{2\pi}\sqrt{(\mu/2(0.002))}} exp(-(x - x^*)^2/(\mu/(0.002)))\partial x$$
$$= \sqrt{2\pi}\sqrt{(\mu/2(0.002))}[\Phi(\frac{x_n^U - x_n^*}{\sqrt{\mu/2(0.002)}}) - \Phi(\frac{-x_n^*}{\sqrt{\mu/2(0.002)}})]$$

Therefore,

$$f_n(x_n) = \frac{exp(-0.002(x_n - x_n^*)^2)/\mu)}{\int_0^{z_n} exp(-0.002(x_n - x_n^*)^2)/\mu)\partial x}.$$
$$= \frac{exp(-0.002(x_n - x_n^*)^2)/\mu)}{\sqrt{2\pi}\sqrt{(\mu/2(0.002))}[\Phi(\frac{x_n^U - x_n^*}{\sqrt{\mu/2(0.002)}}) - \Phi(\frac{-x_n^*}{\sqrt{\mu/2(0.002)}})]} \tag{11}$$

taking the $ln$ of this (for the log likelihood)

$$ln(f_n(x_n)) = -0.002(x_n - x^*)^2/\mu - \frac{1}{2}ln(\frac{\mu}{2(0.002)}) - ln[\Phi(\frac{x_n^U - x_n^*}{\sqrt{\mu/2(0.002)}}) - \Phi(\frac{-x_n^*}{\sqrt{\mu/2(0.002)}})] \tag{12}$$

## A.2. The Censored Model

For the censored assume that $\zeta_n$ is the subjects actual decision and $x_n$ is the observed decision which is constrained to be between 0 and $x_n^U$ so that

$$x_n = \begin{cases} 0 & if\ \zeta_n \leq 0 \\ \zeta_n & if\ 0 < \zeta_n < x_n^U \\ x_n^U & if\ \zeta_n \geq x_n^U \end{cases} \tag{13}$$

Assume that $\zeta_n$ has the logistic distribution assumed for the quantal response model. Then

$$g_n(x_n) = \begin{cases} Prob(\zeta_n \leq 0) & if\ x_n = 0 \\ Prob(0 < \zeta_n < x_n^U) & if\ 0 < x_n < x_n^U \\ Prob(\zeta_n \geq x_n^U) & if\ x_n = x_n^U \end{cases} \tag{14}$$

Thus the likelihood function for the censored logistic distribution is:

$$L = \prod_{x_n=0} \Phi(\frac{-x^*}{\sqrt{2\pi}\sqrt{\mu/2(0.002)}}) \prod_{0<x_n<x_n^U} (\frac{exp(-0.002(x_n - x^*)^2/\mu)}{\sqrt{2\pi}\sqrt{\mu/2(0.002)}}) \prod_{x_n=x_n^U} [1 - \Phi(\frac{x_n^U - x^*}{\sqrt{2\pi}\sqrt{\mu/2(0.002)}})] \tag{15}$$

and the log likelihood is

$$l = \sum_{x_n=0} \ln(\Phi(\frac{-x^*}{\sqrt{2\pi}\sqrt{\mu/2(0.002)}})) + \sum_{0<x_n<x_n^U} [(-0.002(x_n - x^*)^2/\mu) - \frac{1}{2}\ln 2\pi - \frac{1}{2}\ln \mu/2(0.002)]$$
$$+ \sum_{x_n=x_n^U} \ln[1 - \Phi(\frac{x_n^U - x^*}{\sqrt{2\pi}\sqrt{\mu/2(0.002)}})] \tag{16}$$

This is the standard Tobit model ((StataCorp, 1999) Reference A-F p. 146, $\bar{x} = x^*$ and $\sigma = \sqrt{\mu/2(0.002)}$).

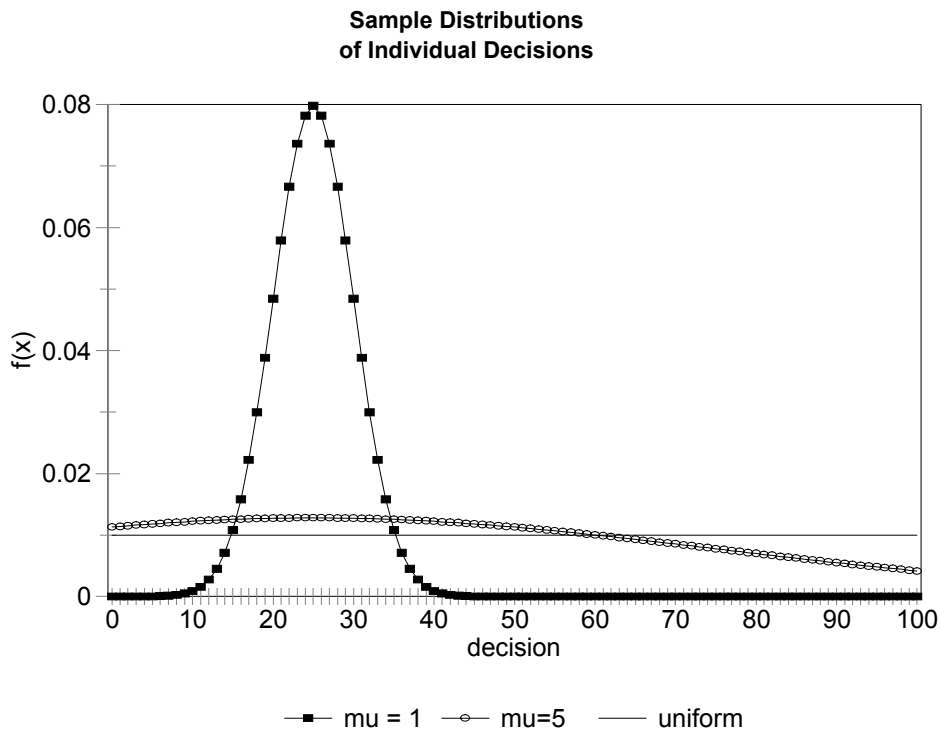


**Figure 1:** Predicted Distributions from the Truncated Logit Quantal Response Model for Medium Capacity Subjects

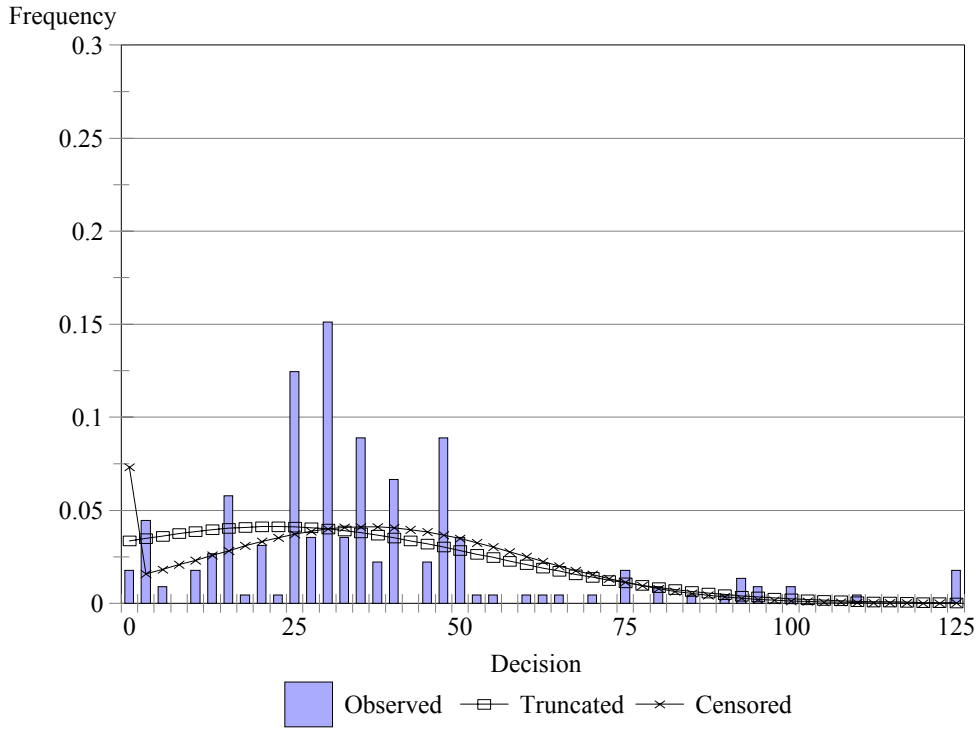


**Figure 2:** Distribution of Individual Decisions and the Predictions of the Truncated and Censored Models, Large Capacity Subjects.

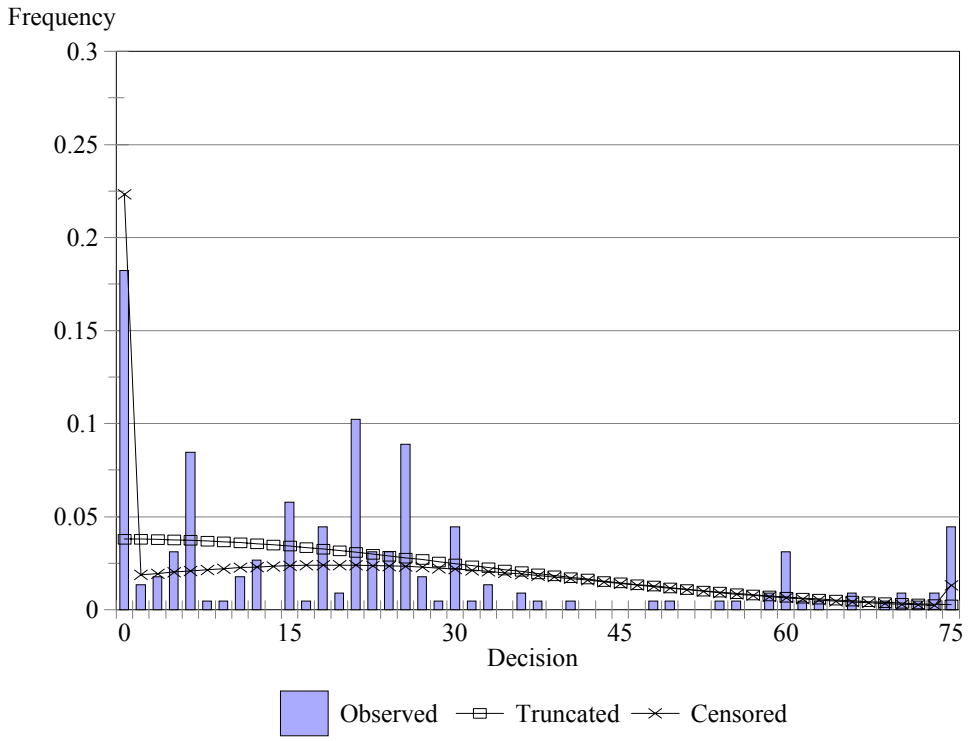


**Figure 3:** Distribution of Individual Decisions and the Predictions of the Truncated and Censored Models, Small Capacity Subjects.

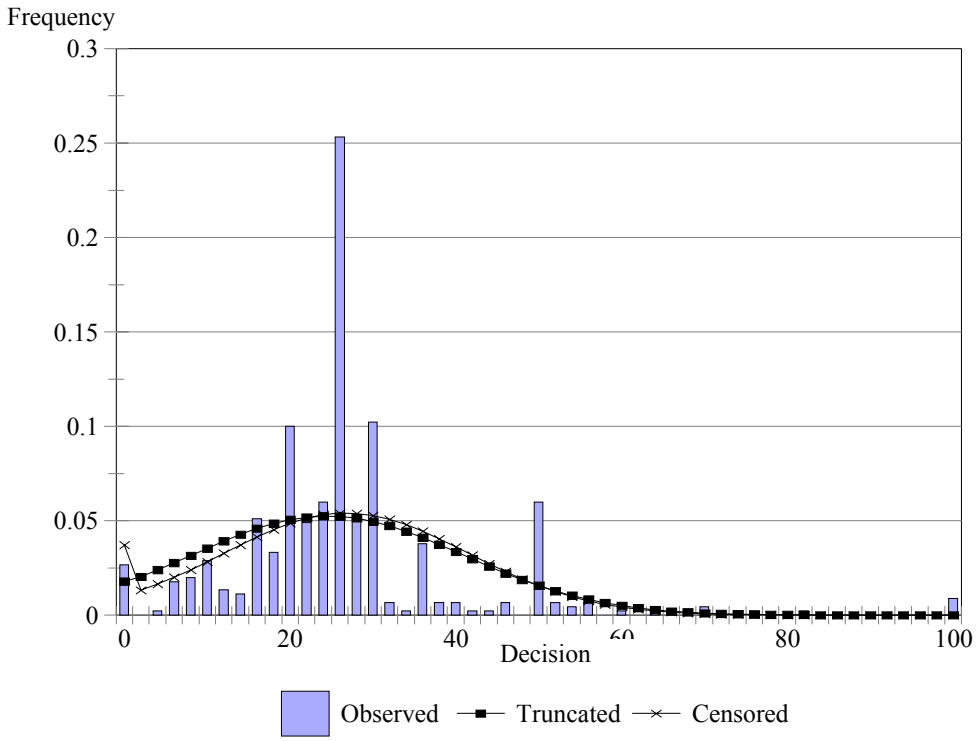


**Figure 4:** Distribution of Individual Decisions and the Predictions of the Truncated and Censored Models, Medium Capacity Subjects.

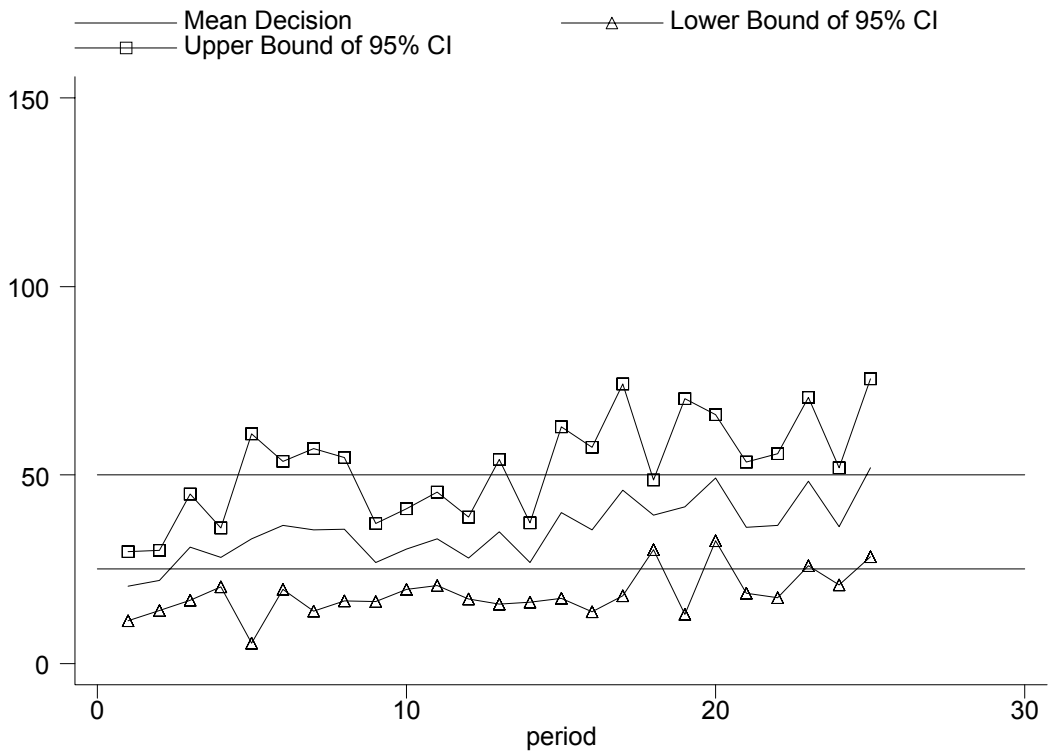


**Figure 5:** Mean Decision Number and 95% Confidence Interval, Large Capacity Subjects.

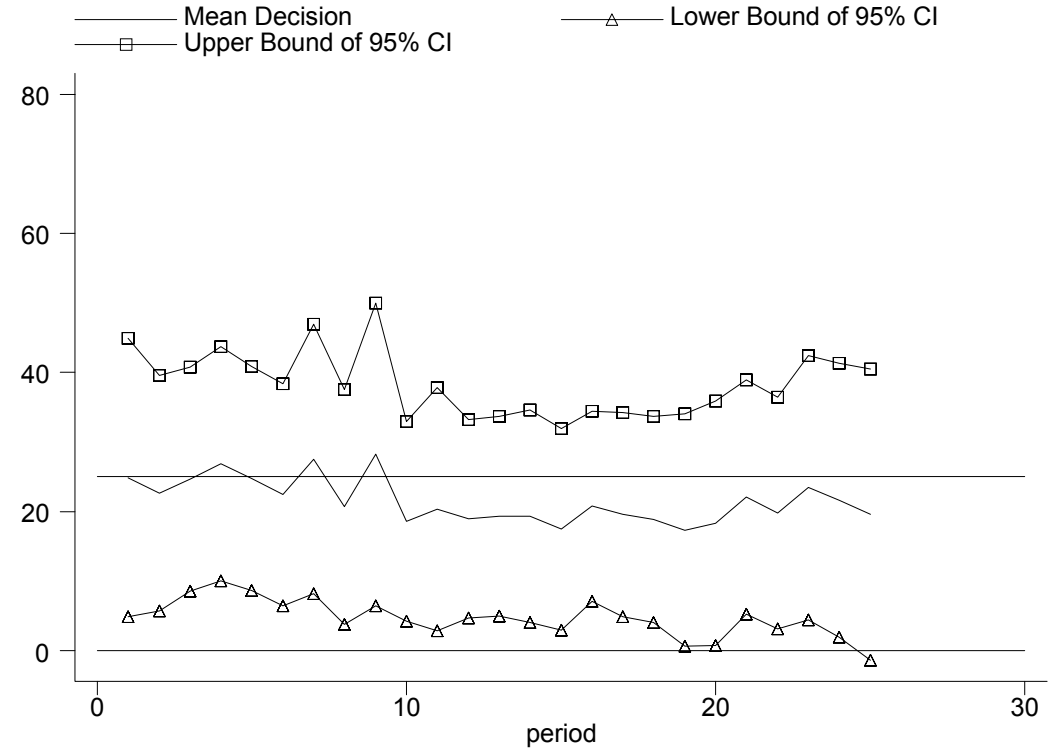


**Figure 6:** Mean Decision Number and 95% Confidence Interval, Small Capacity Subjects.

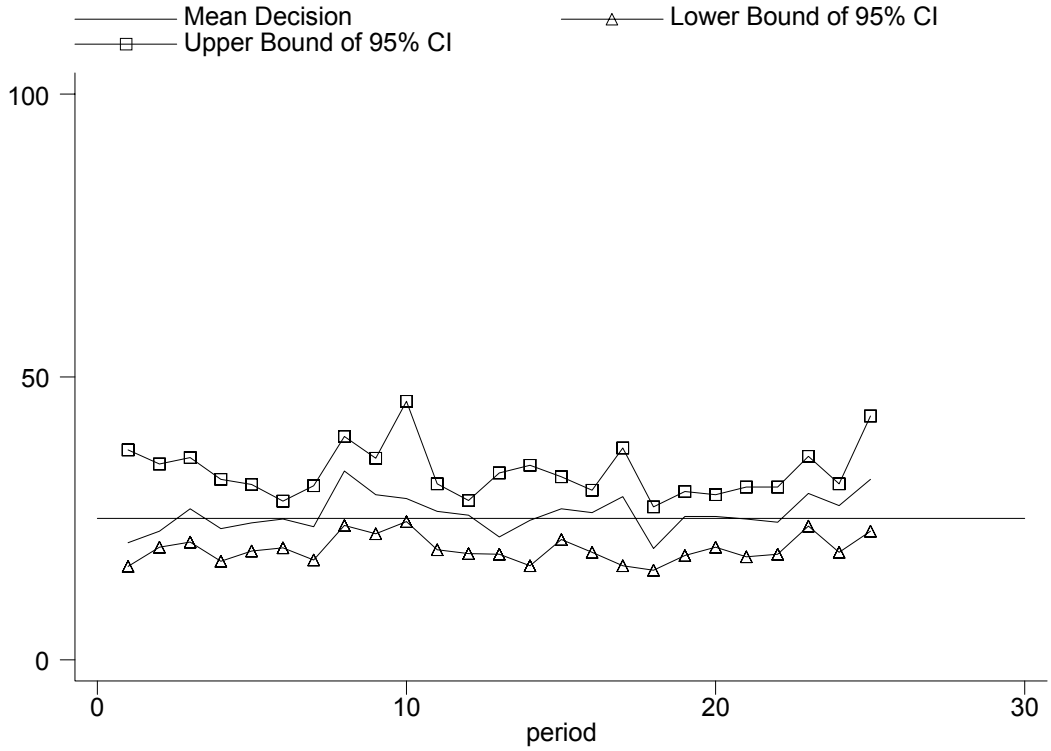


**Figure 7:** Mean Decision Number and 95% Confidence Interval, Medium Capacity Subjects.

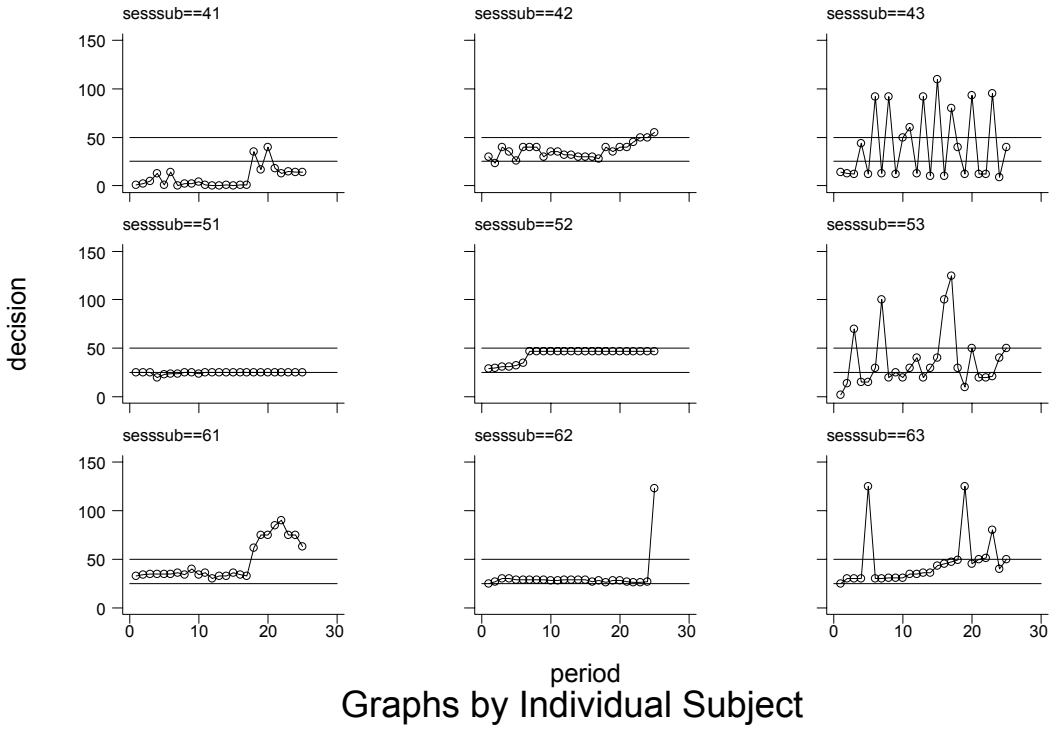


**Figure 8:** Individual Decisions, Large Capacity Subjects.

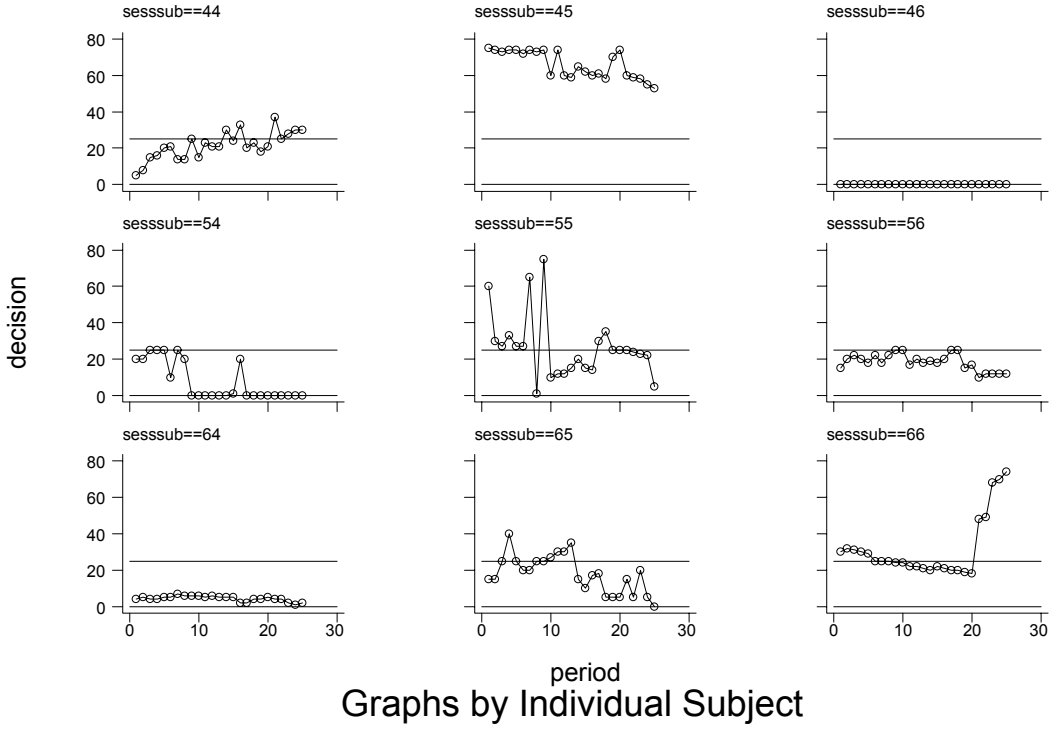


**Figure 9:** Individual Decisions, Small Capacity Subjects.

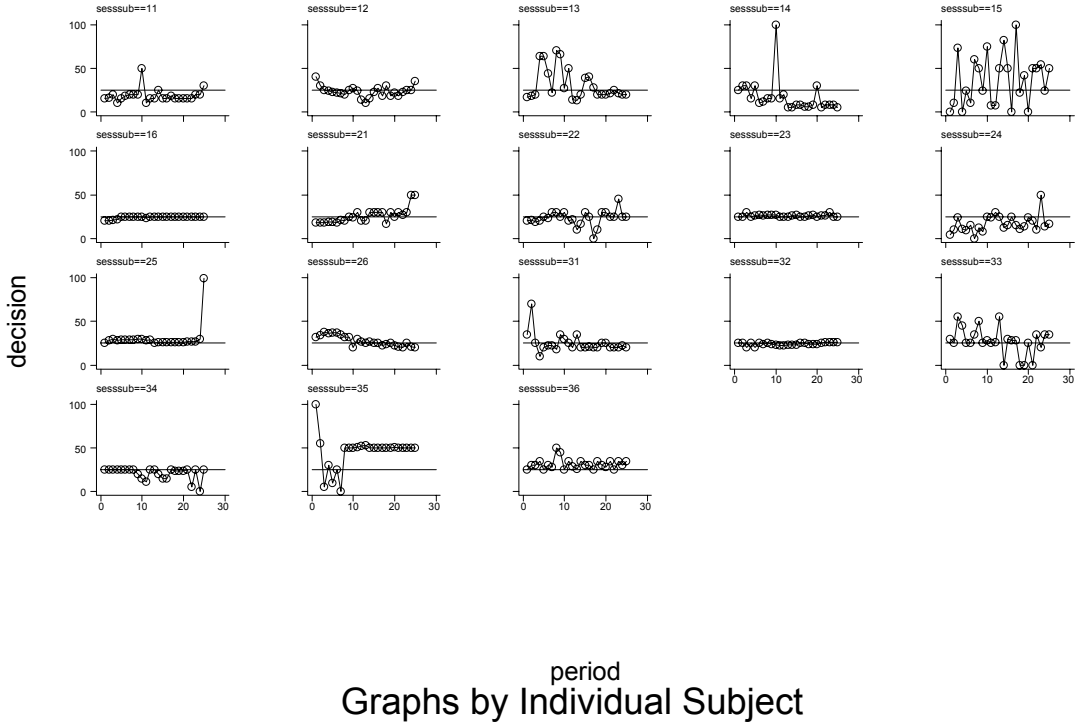


**Figure 10:** Individual Decisions, Medium Capacity Subjects.

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