Eye tracking Social Preferences*

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Preliminary version. Comments welcome

Abstract

We track subjects' eye movements while they make choices in simple three-person distribution experiments. We characterize each subjects in terms of three different types of social preferences: efficiency, maximin, and envy. For the characterization, we use either the choice data or the eye movements data. The hypothesis tested is that if a subject is "really" motivated by a particular social preference, then choosing in accordance with this preference will lead to an identifiable pattern of eye movements. We find that the social preferences inferred from the choices are in line with the choice rule inferred from the eye movements. This gives support for a 'realistic' interpretation of revealed social preferences, and not just an 'instrumentalist' (as if) interpretation.

Keywords: social preferences, experiments, eye tracking, instrumentalism

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1. Introduction

"Despite their key role right at the core of the theory,
the ontological status of preferences
remains quite problematic."
Francesco Guala (2005, p.91)

Over the last decade, several different models have been proposed to describe and explain the evidence for non-selfish behavior (see Fehr and Schmidt, 2006 and Sobel, 2005 for reviews). A prominent class of models assumes that individuals seek to maximize preferences which depend not only on their own income but also on the income of others (e.g., Andreoni and Miller 2002, Bolton 1991, Bolton and Ockenfels 2000, Charness and Rabin 2002, Cox, Friedman, and Sadiraj 2008, Fehr and Schmidt 1999, Levine 1998).

These models can be interpreted in an instrumentalist manner. Agents behave *as if* they maximize a social preference function. The model seeks to predict the choices agents make, but there is no presupposition that the model corresponds to any mental activities involved in making decisions. The success of a preference model is assessed in terms of the correspondence of its predictions to agents' observed choices, and not in terms of the correspondence of its assumptions to processes going on in the mind of the agent. Of course, this is a common position on the role of models and utility functions (Friedman, 1953).

At the same time, it can be noticed that some economists - behavioral and neuro economists in particular - are more ambitious regarding preference models. Their position can be called realism (Guala, 2005). The aspiration is to find models that are not merely *consistent with* choice behavior, but that also *describe* these choices. Posited preferences should not only provide a useful representation of agents' choices, they should also explain these choices in a more causal sense. That is, they should be an input to agents' decision making process.

In the present paper we use eye tracking methodology to examine whether the social preference models mentioned above can live up to the ambition of the realists. The hypothesis tested is that if a subject is 'really' motivated by particular social preferences, then choosing in accordance with these preferences will lead to a distinct pattern of eye movements. The hypothesis is based on the supposition that different choice rules often require different pieces of information to be acquired and processed, which is reflected in different eye movements. Based on this supposition, we perform the following analysis. We track subjects' eye movements while they make choices in a series of three person dictator games of the same type as in Engelmann and Strobel (2004). We classify subjects according to how well their choices fit the choice rules that correspond to three types of social preferences: maximizing efficiency, maximizing the minimum payoff, and minimizing envy. We also classify subjects according to how well their eye movements fit the same set of choice rules. A key design feature that allows us to do so is that we track subjects eye movements while they are *instructed* to choose in accordance with each of these three choice rules. Hence, we know what the eye movements look like when subjects actually use these choice rules. And, indeed, in line with the supposition above, the implementation of the different choice rules leads to identifiably different patterns of eye movements. By comparing those patterns with the eye movements they display when they choose freely (i.e., in line with their preferences) we infer what the subjects "seem to be doing" in the latter case and classify them accordingly. Finally, we compare the classification based on the choice data and the classification based on the eye movements data and assess their correspondence.

The result shows that there is a significant correspondence between the two classifications. If a subject's choices are consistent with a particular type of social preference, this also tends to be reflected in their eye movements. Hence, the eye-movement patterns by and large confirm the revealed preference inferences based on subjects' choices. Loosely put, what subjects appear to be interested in when you look at their choices, corresponds to what they appear to be interested in when you look at their eyes. In this sense, the revealed preferences inferences are not only 'as if', they are also descriptive for the cognitive process underlying the choices. A secondary conclusion we draw is that, notwithstanding the noise in the data, eye tracking delivers meaningful data on the informational input of decisions. In particular, difference preferences lead to distinct, identifiable and intuitive eye movements patterns.

There are several other methods that can be used to generate process data about the cognitive processes that underlie decision making. Relative to neuroscientific methods, such as PET scans or fMRI, eye tracking is relatively cheap and places almost no physical or emotional burden on subjects. Moreover, the data are comparatively easy to analyze and interpret. Eye tracking also has distinctive advantages relative to Mouselab data (Payne et al., 1993) or think-aloud protocols (Russo, Johnson and Stephens, 1989). Eye movements are automatic processes which can be recorded in a non-intrusive way, without exemplifying awareness or inducing purposeful reasoning (Glöckner and Betsch 2008, Lohse and Johnson 2002). Moreover, besides data on what information is being processed and in what order, eye tracking also generates information about the depth of information processing, e.g.,. whether a subject is consciously digesting or merely scanning information (Velichkovsky et al. 2000).

In social science, eye tracking has been mainly used by psychologists and marketing researchers (see e.g., Duchowksi 2007). Recently, also some studies in economics have used eye tracking, for example, to study payoff information acquisition in games (Hristova and Grinberg 2007), learning in games (Knoepfle, Wang, Camerer, 2009), decision making under time pressure (Reutskaja et al., 2009) or the relationship between pupil dilation and deception (Wang, Spezio, Camerer, 2009). The study closest in spirit to ours is Arieli, Ben-Ami and Rubenstein (2009), which investigates eye movements while subjects play two-person allocation games. Their interest is mainly in investigating whether people who make self-interested choices, nevertheless pay attention to the payoffs of the other individual. They find that most subjects do process this information even in case their choices suggest that they are not much concerned with the payoffs of others.

This remainder of this paper is organized as follows. In the next section we outline how the experiment was conducted. In Section 3 we explain how we processed the eye tracking data. Section 4 contains the main analysis in which we confront the choice data with the eye tracking data. In Section 5 we explore some possible explanations for "mismatches" between choices and eye movements. Our conclusion is in Section 6.

2. Experimental Design and Procedure

2.1 Experimental games

Our experiment employs simple three person distribution (dictator) games as in Engelmann and Strobel (2004). The game is presented in the form of a 3 by 3 matrix in which the person 2 (the "dictator") chooses among 3 allocations for the payoffs of 3 persons. Table 1 gives an example of such a game.

Table 1. Three-person dictator game (sample)

	A	B	C
Person 1	11	15	21
Person 2	9	9	9
Person 3	1	7	4

In our experiment, we employ 18 different games (payoff matrices). All games share the following properties. There are three different allocations, A, B, and C; and three persons, 1, 2, 3. Person 2 chooses the allocation that will be implemented. The payoff of person 2 is constant across the three allocations. Person 1 always has the highest payoff, person 2 always has the middle payoff, and person 3 always has the lowest payoff. Appendix A1 gives a complete overview of the game matrices we used.

The fact that the choice of the dictator (person 2) does not affect his or her own payoff allows us (as well as Engelmann and Strobel [2004]) to focus on the social component of preferences. As mentioned above, in the present study we consider the following three choice rules for person 2:

Maxi-sum = maximize the sum of the payoffs

Maxi-min = maximize the minimum payoff (i.e., the payoff of person 3)

Mini-envy = minimize the difference between the highest payoff (i.e., the payoff of person 1) and person 2's own payoff.

These three choice rules are the key components in two prominent social preferences models: Fehr and Schmidt (1999) and Charness and Rabin (2002). The former paper postulates that people get disutility from disadvantageous as well as advantageous inequality, whereas the latter paper hypothesizes that people care for the worst-off person (maxi-min) as well as for the sum of all persons' income (maxi-sum). In our experimental design, maxi-min and an aversion to advantageous inequality overlap, since the person making the decisions always has the middle income and does not have his or her own income at stake (just as in Engelmann and Strobel, 2004). Focusing on these three components of social preferences is a restriction, of course. As will be seen below though, the assumption that a subject chooses in accordance with one and only one of these three choice rules still captures about 86% of the choices overall.

The 18 games we employ differ along three dimensions. First, in 12 games the three different choice rules give conflicting predictions, in 6 games they give overlapping predictions. Second, there are two versions of each game, the only difference being that the allocations A and C are switched. Third, half of the games have relatively weak incentives; in terms of each of the three choice rules the differences between the three allocations are relatively small. In the other half of games the differences between the three allocations are somewhat more pronounced.

2.2 Eye tracking method

We recorded subjects' eye movements while they were choosing among allocations in the different games. These data were generated by means of a Tobii Eye-tracker 1750 using infrared corneal reflection. It consists of a monitor with a build-in camera, which is hidden in a black surface such that it does not distract the subject. With this technology, there is no need for head rests, chin rests or bite bars to prevent a subject's head from moving. Head-motions which are slower than 10cm/s are allowed. Thus subjects can participate in the experiment without feeling constrained. Though the binocular machine records movements from both eyes, it is sufficient that only one of the eyes is within the field of view. At the beginning of the experiment it is necessary to calibrate a subject's eye movements to adjust for individual characteristics before the recording. So a subject is aware of the fact that his or her eye movements are being recorded, but other than that the recordings are non-intrusive.

The eye tracking data were analyzed for fixations using ClearView 2.7.0 software. The fixation filter was set with a fixation radius of 30 pixels and minimum duration of 100ms. The field of view of the camera is about 20x15x20cm (width x height x depth) with our subjects sitting 60cm away from the screen. Eye movements were recorded with remote binocular sampling rate of 50 Hz and an accuracy of about 0.5°. A very convenient feature of ClearView is that it allows so-called areas of interest (AOIs) to be defined in the computer screens that the subjects saw during the experiment. ClearView produces all of the filtered gaze data in the AOI including the starting time of the fixation and the duration. In the analysis, we define a separate AOI for each cell of the matrices with the buffer zones of 30 pixels for 1024*768 screen resolution. Thus, we record how often a subject looks into each cell (fixations frequency), how long he or she looks in the cell (gaze time) and the transitions from one cell to another (saccades).

2.3 Experimental procedure

The experiment was held at CentERlab in Tilburg University, the Netherlands. In total, 46 subjects participated in the experiment. The participants were recruited by means of email lists of students interested in participating in economic experiments. The language used in the experiment was English. Upon arrival, participants were randomly assigned to one of the four cubicles equipped with an eye tracking machine. Subjects participated in the experiment individually and at their own pace.

The experiment consisted of two parts. A complete set of instructions is provided in Appendix A2. In Part 1 the subjects had to choose a preferred allocation as person 2 in each of the 18 games described above (see Appendix A1). The order in which the subjects played the 18 games was determined randomly before the experiment, and was the same for all subjects: 18-11-15-5-7-17-3-6-13-2-12-16-10-1-8-14-4-9. Subjects were informed that upon completion of the experiment, they would be matched to two other participants randomly selected among all participants. They would be randomly assigned to the three roles: Person 1, Person 2, and Person 3. Thereafter, one of the 18 rounds of Part 1 would be randomly selected, and the allocation (A, B or C) chosen by the Person 2 in that round would be implemented. This procedure was carefully explained in the instructions. In particular, it was emphasized that their own decisions could not affect their own earnings.

Upon completion of Part 1, subjects were provided with the instructions for Part 2. In this part subjects were instructed to choose in line with three successive choice rules in 8 games per choice rule. The 8 games used in Part 2 were a random selection from the set of 18 games used in Part 1. Subjects were first instructed to choose the allocation which gives the highest sum of the payoffs (Maxi-sum) in games 12-13-9-8-18-5-4-1, then instructed to choose the allocation which gives highest minimum payoff (Maxi-min) in games 5-13-8-9-18-1-12-4, and, finally, instructed to choose the allocation that gives the lowest difference between the maximum payoff and person 2's payoff (Min-envy) in games 5-13-1-9-8-18-4-12. Subjects were informed that they would receive 0.20 Euro for each "correct" answer in each of the 24 games in Part 2.

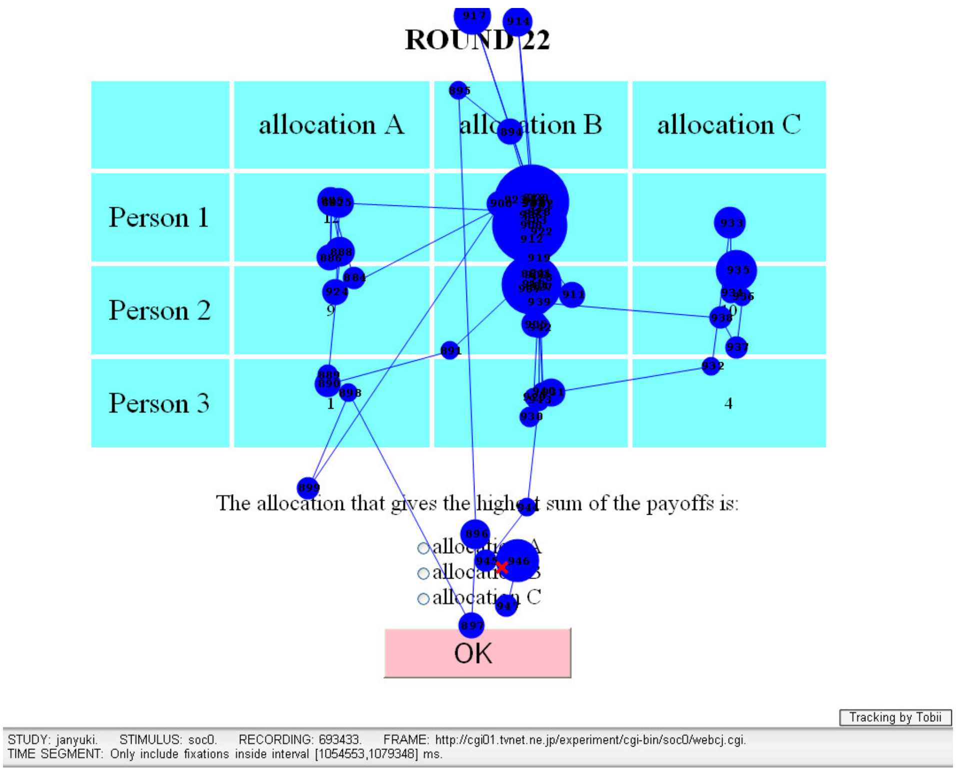
The instruction also included an understanding test to check if a subject understood the task. The instructions were provided to subjects on paper. The rest of the experiment was computerized. The subjects were presented with a sequence of screens on the computer monitor which each contained one game and one corresponding question. See Appendix A3 for a sample screen. In total each subject made 42 decisions; 18 of these were preference based and 24 were rule based. The experiment lasted about 30 minutes on average. Participants earned on average 15 Euro including 2 Euros participation fee.

3. Eye tracking data

3.1 Processing the raw data

In each round, subjects see a payoff matrix as the one in Figure 1 where the three allocations A, B and C are displayed column-wise and the three rows correspond to the payoffs to “Person 1”, "Person 2", and “Person 3”, respectively. We define 9 areas of interests (AOIs hereafter) around the 9 payoffs. For each subject and each round, we have information on how often (fixation count) and how long (gaze time) a subject gazed in each of the AOIs. The two variables, however, are strongly correlated and in the remainder of the paper we will focus in the gaze time data. We also counted the so-called saccades, that is, transitions from one fixation to the next. As we have 9 AOIs, and we do this in both directions, including those within the AOIs, this amounts to 81 different directed saccades. The dots in Figure 1 illustrate a fixation, the size of the dot illustrates the corresponding gaze time, and the lines between two dots depict a saccade, where it should be noted that fixations and saccades outside the AOIs around the payoff cells are not included in the analysis.

Figure 1. Areas of Interest, Fixations, and Saccades



From the raw fixations data we construct two types of variables to characterize the pattern of eye movements of a subject in a particular round based on gaze time and saccades, respectively. First, we construct three variables GAZE_ROW_i, measuring for each row (i = 1, 2, 3) the proportion of the total gaze time spent in the three AOIs in that row. So, these three variables measure the relative time spent looking at the payoffs of persons 1, 2, and 3, respectively. Note that the three gaze time variables add up to 1.[1] Second, we construct five

[1] Note that we do not use variables that refer to specific columns. Previous research has shown that people tend to display a gaze bias towards the option they will eventually choose. If a subject looks a lot at a specific column this is informative for the allocation the subject will eventually chooses

variables relating to the saccades. The first variable SAC_WITHIN_ROWS measures the saccades that go within rows, that is, from the payoff of a person in one allocation to the payoff of the same person in another allocation. Second we measure the saccades that go across rows, that is, from a payoff of one person to the payoff of another person. In the latter case, we make a further distinction depending on which rows (persons) are being compared (rows 1 and 2, rows 1 and 3, or rows 2 and 3) but we do not distinguish the direction of the saccade. This gives the following variables: SAC_ BETWEEN_ROWS12, SAC_ BETWEEN_ROWS13, and SAC_BETWEEN_ROWS23 .[2] Finally, there is a rest category which contains the saccades that remain within the same AOI: SAC_ WITHIN_AOIS. For each of these five categories of saccades, the corresponding variable measures the fraction of all saccades that falls within that category. So, the five saccades variables sum to one.

Table 2. Summary statistics of the eye movements variables

	Part 1	Part 2			
	Choices (1-18)	Overall (19-42)	Maxi-Sum (19-26)	Maxi-Min (27-34)	Mini-Envy (35-42)
GAZE_ROW_1	0.43(0.20)	0.45(0.20)	0.53(0.18)	0.27(0.21)	0.55(0.21)
GAZE_ROW_2	0.39(0.20)	0.39(0.20)	0.44(0.22)	0.34(0.17)	0.37(0.20)
GAZE_ROW_3	0.18(0.15)	0.17(0.15)	0.14(0.12)	0.29(0.23)	0.08(0.10)
SAC_WITHIN_ROWS	0.28(0.21)	0.29(0.23)	0.18(0.16)	0.33(0.27)	0.35(0.27)
SAC_BETWEEN_ROWS12	0.34(0.24)	0.37(0.25)	0.40(0.23)	0.24(0.24)	0.46(0.27)
SAC_BETWEEN_ROWS23	0.13(0.17)	0.09(0.15)	0.15(0.19)	0.09(0.16)	0.03(0.09)
SAC_BETWEEN_ROWS13	0.14(0.18)	0.12(0.16)	0.10(0.14)	0.20(0.22)	0.06(0.11)
SAC_WITHIN_AOIS	0.11(0.16)	0.13(0.17)	0.15(0.21)	0.16(0.17)	0.11(0.15)

Note: The averages of each variable in Part 1 and Part 2 are presented, with standard deviations in parentheses.

Table 2 displays averages and standard deviations for the different eye movements variables. The table distinguishes between Part 1 (rounds 1-18), in which subjects choose the

(Shimojo et al., 2003). However, in our analysis we wish to rely only on eye gaze information that is related to the social preferences of the subject and the structure of the information patterns that come with it.

[2] For the saccades that occur within rows we do not make a further distinction depending on the row within which the saccade occurs. The reason is that doing so would cause the three within-row saccade variables to be strongly correlated with the corresponding three GAZE_ROW variables.

allocation they prefer, and Part 2 (rounds 19-42) in which subjects are instructed to choose in line with the three different choice rules. A notable feature of the data is that the averages of all variables are quite similar for Part 1 (column 2) and Part 2 (column 3). Moreover, comparing the averages across the three different rules (columns 4 - 6) displays several intuitive features. For example, when subjects are induced to choose in line with Maxi-sum (fourth column) they display relatively few within row saccades. This makes sense since Maxi-sum induces subjects to sum payoffs for each allocation and hence requires relatively many saccades within columns (i.e., between rows). Another intuitive feature is that Maxi-min induces relatively much gaze time in row 3, that is, the row containing the payoffs of person 3 who always has the lowest payoff. A more systematic analysis of the differences that identify the different choice rules is contained in the next subsection.

3.2 Multinomial Logit model

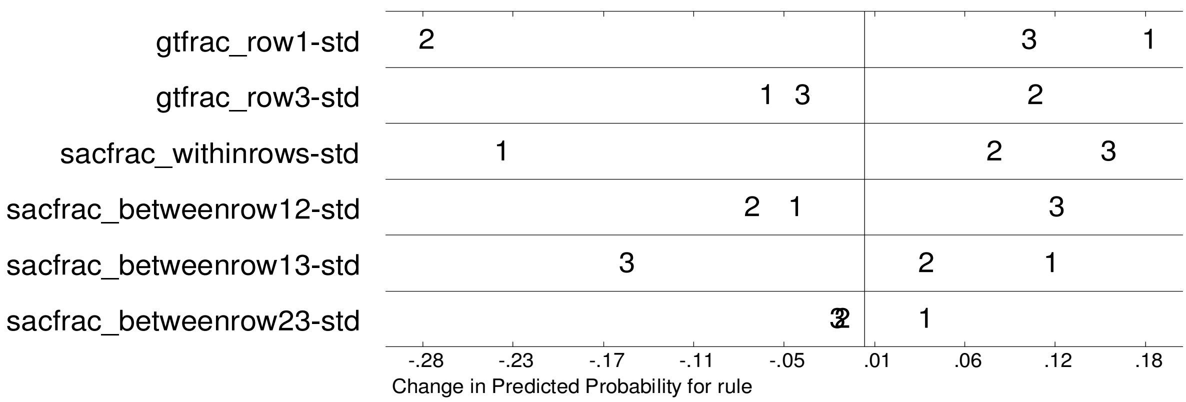
We now try to identify the distinct eye movement patterns that correspond to the three different choice rules. As mentioned above, in Part 2 of the experiment, we instruct the subjects to choose an allocation in accordance with Maxi-sum, Maxi-min and Mini-envy, respectively. Each choice rule is imposed for eight rounds. We examine whether the eye movements data, as summarized in the eight variables just described, can predict which choice rule is being used. Hence, the dependent variable, denoted by C_{it}, is the choice rule that subject i (i = 1, ..., 46) uses in round t (t = 19, ..., 42), where C_{it} takes the value 1 (Maxi-sum) in rounds 19-26, 2 (Maxi-min) in rounds 27-34, and 3 (Mini-envy) in rounds 35-42. The explanatory variables are the eight eye movements variables, denoted by the vector E_{it}. So the following model is estimated:

$$\Pr(C_{it} = k) = \frac{\exp(E'_{it}\beta_k)}{1 + \sum_{j=1}^{2} \exp(E'_{it}\beta_j)} \qquad for \quad k = 1,\ 2$$

$$\Pr(C_{it} = 3) = \frac{1}{1 + \sum_{j=1}^{2} \exp(E'_{it}\beta_j)}$$

Table B1 in Appendix B presents the details of the estimated model. Here we only discuss some of the main features. Figure 2 displays the effect of a one standard deviation change of the explanatory variables on the predicted probability that a particular choice rule is used. The estimated effects are quite intuitive overall. For instance, the second row indicates that an increase in GAZE_ROW_3 increases the predicted probability that rule 2 (Maxi-min) is being used by about 10%. This reflects the fact that implementing Maxi-min requires relatively much attention to be directed at Row 3 which contains the payoff information of the person with the lowest payoff (Person 3). We also see, for example, that a one standard deviation increase in SAC_BETWEEN_ROWS12 increases the predicted probability that rule 3 (Mini-envy) is used by about .40. Again this makes good sense as Mini-envy involves a comparison between the payoffs of Person 1 and Person 2. An increase in SAC_BETWEEN_ROWS13, on the other hand, is associated with an increase in the use of rule 2 (Maxi-sum) and a decrease in the use of rule 3 (Mini-envy). This is in line with the intuition that Maxi-sum requires adding up rows 1 and 3 in particular (as the value of row 2 is fixed) and that for Mini-envy there is no need to look at row 3 or to make comparison with row 3. There are also some less intuitive effects. For example, it is not so clear why an increase in the fraction of within row saccades (SAC_WITHIN_ROWS) is associated more strongly with rule 3 (Mini-envy) than with rule 2 (Maxi-min) as one might expect that the latter only requires comparisons within rows (row 3 in particular). Still, overall there is a clear structure in the eye movements data and this structure is much in line with what one might expect. Moreover, the fit of the model is quite good. In 86% of the cases it correctly predicts the choice rule that is being implemented.

Figure 2. Change in Predicted Probability



Notes: There are six explanatory variables listed on the left; the other two are redundant because the three GAZE_ROW variables sum to one, as do the five SAC variables. The horizontal axis represents the change in the predicted probability that each rule is being used given a one-standard deviation increase of the explanatory variable. The numbers identifying the choice rules are 1=Maxi-sum, 2=Maxi-min, and 3=Mini-envy.

4. Main Analysis

Our main analysis proceeds in three steps. First, we classify each subject on the basis of her or his choices in Part 1 of the experiment. Second, we classify each subject on the basis of her or his eye movements in Part 1. Finally, we compare the two classifications and examine how well they correspond.

Each subject makes 18 choices in Part 1. For each subject (i = 1,.., 46) we calculate the fraction of choices that is in line with Maxi-sum (f_i^1), Maxi-min (f_i^2), and Mini-envy (f_i^3), respectively.[3] We call the preference rule that best describes a subject's choices the dominant rule ($\arg\max_{k\in\{1,2,3\}}\{f_i^k\}$) and classify the subject accordingly. Table 3 shows the distribution of the dominant rule for the 45 subjects.[4] It turns out that for a majority of the subjects in our experiment the Maxi-min rule best describes their choices. Still, there are also substantial numbers of subjects that are best described by Maxi-sum or Mini-envy.

Table 3. Classification based on choices

Dominant rule (choice data)	# subjects	Consistent choices
Maxi-sum	10	164/180 91%
Maxi-min	26	420/468 89%
Mini-envy	9	122/162 75%
Total	45	706/810 86%

The last column indicates what fraction of choices is actually consistent with the dominant rule. In principle, a rule can be the dominant rule of a subject with as little as 28%

[3] Recall that in 6 of the 18 rounds, the prescriptions of the three rules overlap. Therefore, these fractions do not generally add up to one.
[4] For one subject there was a tie between two rules and we exclude this subject from the analysis.

(5/18) of the choices being consistent with it.[5] It turns out though that the dominant rules capture the choices quite well. For example, for the subjects for which Maxi-sum is the dominant rule, 91% of the choices is in line with this rule. Overall, 86% of the choices are consistent with the dominant rule. This suggests that our focus on these three basic preferences rules is less restrictive than it might seem.

We use a similar procedure to classify subjects on the basis of their eye movements in Part 1 of the experiment. We determine the choice rule that best describes a subjects eye movements. For each subject *i* (i = 1, ..., 45) and each round *t* (t = 1, ..., 18) we feed the eye movements data (E'_{it}) into the estimated logit model, discussed in the previous section. This generates the predicted probabilities p_{it}^{k} that subject *i* is using rule *k* in round *t* (with k = 1, 2, 3). We classify each subject *i* in accordance with the rule the subject is most strongly predicted to use over the 18 rounds (arg max $_{k\in\{1,2,3\}}$ $\{\frac{1}{18}\sum_t p_{it}^{k}\}$).

Table 4. Classification based on choices and eye movements

Dominant rule based on choices	Dominant rule based on eye movements			
	Maxi-sum	Maxi-min	Mini-envy	Total
Maxi-sum	8	2	0	10
Maxi-min	9	16	1	26
Mini-envy	1	4	4	9
Total	18	22	5	45

Pearson Chi-square (4) = 20.01, $p < .001$; Kappa = 0.38, $p < .001$

The final step is to confront the classification based on choices with the classification based on eye movements. Table 4 shows the correspondence between the two classifications. The most important feature of the table is the number of subjects on the diagonal. For 62% of the subjects (28 out of 45) the two classifications correspond to each other. This is much higher than the percentage (33%) that could be expected if the two classifications were independent. This correspondence is highly significant, both with Pearon's Chi-square test for

[5] Recall that in 6 of the 18 games the prescriptions of the three preference rules overlap. In these games all 6 choices could be inconsistent with any of the three rules. If in the remaining 12 games, 5 choices are in line with rule k, 4 in line with rule k', and 3 in line with rule k'', then k is the dominant rule while only 5 out the 18 choices are in line it.

independence ($p < 0.001$) and with Cohen's Kappa test for agreement between classifications ($p < 0.001$). This indicates that the inferences we can draw about preferences on the basis of choice data are significantly corroborated by the eye movements. If the choice data suggest that a subject is motivated by a certain type of preferences, the information acquisition process revealed by the eye movements often matches this motivation. We would argue that this provides substantial support for a descriptive interpretation of the revealed social preferences and not merely an instrumental ("as if") interpretation.

Still, for 17 of the 45 subjects the two classifications do not correspond. In the next section, we dig a bit deeper into the possible explanations for these mismatches. Before that, we briefly discuss some robustness checks we performed.

First, we experimented with other specifications of the multinomial logit model, discussed in the previous section. Although the model used for the main analysis makes good intuitive sense, it involves some more or less arbitrary choices. For one thing, we used Gaze Time - how long subjects look at a particular area - to measure the attention addressed at the respective rows (i.e., players) in the payoff matrix. An alternative measure is to use Fixation Counts, that is, how often subjects look at particular areas. It turns out that the analysis is robust to using Fixation Count rather than Gaze Time. The classification remains exactly the same. We also examined whether the inclusion of both Gaze Time variables (measuring attention) and Saccades variables (measuring comparisons) are essential. This turns out to be the case indeed. The correspondence between choice data and eye movements data is substantially stronger when both pieces of information are included in the logit model.[6]

Another check we performed is to base the classification only on the second time subjects were confronted with a particular game. Recall from the design section, that in Part 1 subjects processed 18 payoff matrices of which only nine were structurally different. Subjects essentially played each game twice, with the only difference being that the columns were re-ordered. If we base the classification on the data of the second game only, the fit between the two classifications improves. Now for 30 of the 45 subjects (67%) the choice data and the eye movements data identify the same dominant rule. The more experienced subjects are with a particular game, the better the fit between choice and process data.[7]

[6] Adding information about the column gaze times, would further improve the correspondence between the two classifications, but we belief this would not be for structural reasons. See also footnote 1.

[7] The correspondence does not improve though if we focus on rounds 10 to 18 rather all rounds, as in the main analysis.

Another question we addressed is whether the 'strength' of the eye movements information mattered. We analyzed whether the correspondence is better for subjects for whom the eye movements data provide stronger evidence on the choice rule they appear to be using. The classification over the columns of Table 4 is based on the prediction derived from the logit model. This prediction (max $_{k\in\{1,2,3\}}$ $\{\frac{1}{18}\sum_t p_{it}^k\}$) varies substantially over the 45 subjects. So we can do a median split and divide the subjects into those with relatively strong evidence on the rule they implement and those with relatively weak evidence. It turns out that the correspondence between choice data and eye movements data is substantially stronger among the former group of subjects (73%) than among the latter group (52%). The stronger the evidence obtained from the eye movements data, the closer the fit to the choice data.

Overall, these analyses provide support for the robustness of our main result that there is significant and meaningful relationship between the choice data and the eye movements data.

5. Exploring the misclassifications

What is the reason that for 17 subjects the two classifications do not match? This question is not easy to answer. Still the data provide some hints. In this section we briefly explore some possible explanations.

First, it is noteworthy that in a majority of the mismatches (9/17) the choice data indicate that a subject is using Maxi-min, while the eye movements suggest that the subject is using Maxi-sum. Maybe in the early rounds of the experiment subjects are extensively 'scanning' the payoff matrix even though in the end they choose in line with Maxi-min. Is it possible that the logit model identifies such scanning, mistakenly, with the application of the Maxi-sum rule? We find very little support for this possibility. Even though subjects use much more time to make up their mind in the early rounds than in later rounds, the structure of the eye movements, as captured by the gaze time and saccades variables, does not show any clear or significant development over time. In line with this, the eye movements do not predict more Maxi-sum (measured by p_{it}^1) in earlier rounds than in later rounds. The predictions are fairly stable over the rounds. So, we find no evidence that extensive browsing or scanning in early rounds causes the Maxi-min rule to be overpredicted by the eye movements.

A second possibility is that some misclassifications are related to the fact that subjects have other social preferences than the three basic types we allow. One indication for this is that subjects sometimes make choices which are not in line with any of the three rules we consider. Of the 18 games, there are 6 games for which the predictions of the three rules overlap, that is, there is one allocation which is both Maxi-min, Maxi-sum and Mini-envy. Still, there are 15 subjects who at least once make a choice which is not in line with this allocation.[8] Of these 15 subjects there are 7 (47%) for which the dominant rule inferred from the choices corresponds to the dominant rule inferred from the eye movements (i.e., who are on the diagonal of Table 4). Of the other 30 subject, there are 21 (70%) for whom the classifications overlap. This difference between the two groups of subjects is (weakly) significant ($p < 0.10$, with one-sided Chi-square test). This suggests that one reason for the misclassifications is that some subjects, at least sometimes, display preferences which are not captured by any of the three rules we consider.

A related possibility is that the subjects may have preferences which are a (linear) combination of the preferences we consider, such as quasi-maximin (a combination of Maxi-min and Maxi-sum) or inequality aversion (a combination of Max-min and Mini-envy). Subjects who use a combination of preferences may be less easy to classify. Their choices may be in line with one preference (e.g., Maxi-min) for some games, and in line with another preference (e.g., Maxi-sum) for other games. To examine this possibility, we divide the subjects into two groups: those for whom one of the three types of social preferences we consider is enough to describe their choices, and a group of subjects whose choices are consistent with one preference in one set of games and with another preference in another set of games.[9] The former group consists of 24 subjects and for 15 of them (63%) the classification based on choices and the one based on eye movements correspond. The latter group consists of 21 subjects and for 13 of them (62%) the two classifications correspond. There is little difference between the two groups in this regard. Hence, we find no support for the hypothesis that the mismatch between eye movements data and choice data is due to the fact that the social preferences of some subjects are best described by a combination of the preferences we consider.

A fourth explanation for the mismatches in Table 4, is that some subjects make choices which are inconsistent or contain some element of randomness. Recall that subjects

[8] Typically, the allocation they choose in these cases is "competitive" in the sense that it minimizes the sum of payoffs allocated to Persons 1 and 3.

[9] Here we focus on the 12 games for which the three considered preferences lead to different choices.

are confronted with two versions of each of the nine different payoff matrices, where the only difference is that columns 1 and 3 are switched. If a subject chooses consistently, he or she prefer the same allocation in these two versions of the same game. Arguably, if subjects do not make choices consistently it will be harder to classify them unambiguously, both in terms of their revealed preferences and in terms of their eye movements. The data suggest that the match between the two classifications (Table 4) is somewhat weaker for the inconsistent subjects than for consistent ones. There are 24 subjects who make an inconsistent choice at least once, and for 13 of these (54%) the two classifications correspond. Of the 21 consistent subjects, there are 15 (71%) for whom the classifications correspond. Although this difference between the two groups is not statistically significant (p = .117 one-sided, with a Chi-square test), it hints at the possibility that inconsistent subjects are harder to capture consistently on the basis their choices and their eye movements.

Summarizing, we find some support for the hypothesis that the correspondence between choice and process data in our experiment is hindered by the fact that some subjects seem to be acting on preferences which we do not consider, as well as for fact that some subjects simply act inconsistently.

6. Concluding discussion

In this paper we classify subjects' social preferences on the basis of two types of information: choices and eye movements. We find a significant correspondence between the two classifications. If a subject's choices are best described by a particular preference then, in many cases, the visual process of information acquisition also suggests that the subject is acting in line with that preference. We conclude that this gives substantial support for a 'realistic' interpretation of social preferences models, over and above a mere 'instrumentalist' prespective. The revealed social preferences do not only describe choices in an 'as if' manner, they actually appear to be the motivational drivers behind these choices.

The correspondence between choice and process data, though significant, is less than perfect. Still, we tend to argue that the observed correspondence can be regarded as substantial and meaningful. The test we perform is quite ambitious. The classification based on the eye movements relies entirely on subjects' visual inspection of the payoff matrix. The fact that this alone allows for reasonably accurate inferences on subjects' revealed preferences can be regarded as remarkable, especially in view of the noise that typically accompanies both choice and process data. In any case, our analysis indicates that there is a meaningful structure in the eye movements data.

Finally, we would like to emphasize one innovative aspect of our design. Subjects' eye movements are recorded not only when they choose among allocations freely, but also when they are induced to choose in line with the choice rules that correspond to the different types of social preferences. In the latter case we know which choice rule subjects use, and we can compare subjects' eye movements in this case with the former case in which they choose freely. This allows for an assessment of the descriptive realism of the revealed preferences. In principle, this procedure can also be applied to other areas of interest such as cognitive sophistication or learning.

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Appendix A1. Payoff matrices

1	A:ME	B:Mm	C:MS
Person 1	11	15	21
Person 2	9	9	9
Person 3	1	7	4

2	A:MS	B:Mm	C:ME
Person 1	21	15	11
Person 2	9	9	9
Person 3	4	7	1

3	A:ME	B:Mm	C:MS
Person 1	10	15	21
Person 2	9	9	9
Person 3	1	7	4

4	A:MS	B:Mm	C:ME
Person 1	21	15	10
Person 2	9	9	9
Person 3	4	7	1

5	A:ME	B:Mm	C:MS
Person 1	12	15	21
Person 2	9	9	9
Person 3	1	8	4

6	A:MS	B:Mm	C:ME
Person 1	21	15	12
Person 2	9	9	9
Person 3	4	8	1

7	A:ME	B:Mm	C:MS
Person 1	12	15	21
Person 2	9	9	9
Person 3	1	9	4

8	A:MS	B:Mm	C:ME
Person 1	21	15	12
Person 2	9	9	9
Person 3	4	9	1

9	A:ME	B:Mm	C:MS
Person 1	12	15	22
Person 2	9	9	9
Person 3	1	7	4

10	A:MS	B:Mm	C:ME
Person 1	22	15	12
Person 2	9	9	9
Person 3	4	7	1

11	A:ME	B:Mm	C:MS
Person 1	12	15	23
Person 2	9	9	9
Person 3	1	7	4

12	A:MS	B:Mm	C:ME
Person 1	23	15	12
Person 2	9	9	9
Person 3	4	7	1

a	A:*	B	C
Person 1	12	13	15
Person 2	9	9	9
Person 3	8	4	2

b	A	B	C:*
Person 1	15	13	12
Person 2	9	9	9
Person 3	2	4	8

c	A:*	B	C
Person 1	11	13	15
Person 2	9	9	9
Person 3	8	5	2

d	A	B	C:*
Person 1	15	13	11
Person 2	9	9	9
Person 3	2	5	8

e	A:*	B	C
Person 1	11	13	16
Person 2	9	9	9
Person 3	8	4	2

f	A	B	C:*
Person 1	16	13	11
Person 2	9	9	9
Person 3	2	4	8

Appendix A2. Experimental Instructions

Welcome to our experiment. If you follow the instructions carefully you can earn a considerable amount of money. You will get 2 Euro as a show-up fee. How much you earn in addition to that will partly depend on the decisions you make in the experiment. You can collect your earnings, privately and in cash, in room K412 from March 24 - March 26 (10:00-16:00). The experiment consists of two parts.

Part 1

Part 1 consists of 18 rounds. In each round, the computer screen will show a table with three different allocations: allocation A, allocation B, and allocation C. Each allocation involves three amounts - which we will call payoffs - to three different persons: person 1, person 2 and person 3. Here is an example:

	allocation A	allocation B	allocation C
person 1	6	3	10
person 2	4	4	5
person 3	1	7	2

In the example, allocation A implies that person 1 gets a payoff of 6 Euro; person 2 gets a payoff of 4 Euro and person 3 gets a payoff of 1 Euro. Similarly, the table displays the payoffs implied by allocations B and C.

Your task in each round is to decide which of the three allocations A, B, or C you prefer the most, if you would receive the payoff of person 2, and two other participants in the experiment would receive the payoffs of person 1 and person 3, respectively.

Here is how your earnings for part 1 will be determined.

1. After the experiment, you will be matched with two other participants whom we randomly select from participants to this experiment.
2. You will not get to know the identity of the other two participants, nor will the others be able to identify you.
3. We will randomly assign you and the other two participants to the three roles: person 1, person 2, and person 3. So, one of you will be person 1, another will be person 2, and the other will be person 3.

4. We will randomly choose one of the 18 rounds, and implement the preferred allocation (A, B or C) of person 2 for that round. The payoffs corresponding to that allocation determine your earnings.

Note that your preferred allocation for the selected round only matters if you are assigned to the role of person 2. If you are assigned to the role of person 1 or person 3, your own decision is irrelevant to your earnings, as the earnings are determined by the decision of person 2.

Here are some questions to test your understanding.

- Suppose you are assigned the role of person 2, and the round selected for payment involves the table above. How much would you receive as payment if you have opted for allocation C? [   ]
- Suppose you are assigned the role of person 2, and the round selected for payment involves the table above. How much would person 1 receive as payment if you have opted for allocation A?
  [   ]
- Suppose you are assigned the role of person 1, and the round selected for payment involves the table above. How much would you receive as payment if person 2 has opted for allocation B?
  [   ]

Please let us know when you have finished the test questions, so we can check them.
This completes the instructions for Part 1. It is very important that you understand the way the earnings are determined. If something is not crystal clear to you, please do not hesitate to ask.

After the completion of Part 1, you will receive the instruction for Part 2. In the second part, your earnings will not depend on the decisions of other participants. It is rather a quiz in which you can earn money by giving the correct answer.

Instructions for Part 2

Part 2 consists of 24 rounds. In each round you will be asked a question. For each correct answer you will receive 20 Eurocents.

Just as in part 1, for each round the computer screen will show a table with three different allocations: allocation A, allocation B, and allocation C. Here is an example:

	allocation A	allocation B	allocation C
person 1	6	3	10
person 2	4	4	5
person 3	1	7	2

You will be asked a question about the allocations. The questions will be of three different types.

1. Which allocation gives the highest sum of the payoffs?
2. Which allocation gives the lowest difference between the maximum payoff and person 2's payoff?
3. Which allocation gives the highest minimum payoff?

For the example above, the correct answers would be as follows:

1. The sum of the payoffs is 6+4+1=11 for allocation A, 3+4+7=14 for allocation B, and 10+5+2=17 for allocation C. Therefore, the allocation that gives the highest sum of the payoffs is: allocation C.
2. The difference between the maximum payoff and person 2's payoff is 6-4=2 for allocation A, 7-4=3 for allocation B, and 10-5=5 for allocation C. Therefore, the allocation that gives the lowest difference between the maximum payoff and person 2's payoff is: allocation A.
3. The minimum payoff is 1 for allocation A, 3 for allocation B, and 2 for allocation C. Therefore, the allocation that gives the highest minimum payoff is: allocation B.

Here are some questions to test your understanding:

	allocation A	allocation B	allocation C
person 1	2	7	11
person 2	5	5	3
person 3	6	3	2

1. Which allocation gives the highest sum of the payoffs? Allocation [ ]
2. Which allocation gives the lowest difference between the maximum payoff and person 2's payoff? Allocation [ ]
3. Which allocation gives the highest minimum payoff? Allocation [ ]

Please let us know if you have completed the three test questions.

As stated above, you will be asked in total 24 questions and you will receive 20 Eurocent for each correct answer. Upon the completion of part 2, you click “OK” on the final screen. Then the experiment ends and you can leave the cubicle**.**

Thank you for participating in our experiment.

Appendix A3. Sample Screens

Part 1

ROUND 1

	allocation A	allocation B	allocation C
Person 1	16	13	11
You (Person 2)	9	9	9
Person 3	2	4	8

Which allocation do you prefer the most?

- allocation A
- allocation B
- allocation C

OK

Part 2

ROUND 19

	allocation A	allocation B	allocation C
Person 1	23	15	12
Person 2	9	9	9
Person 3	4	7	1

The allocation that gives the highest sum of the payoffs is:

- allocation A
- allocation B
- allocation C

OK